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FORECASTING NAVY ISSUE AND RECEIPT WORKLOAD AT DEFENSE LOGISTICS AGENCY DEPOTS

by

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Each year the Defense Logistics Agency (DLA) asks the military services to estimate their future issue and receipt workload demands at DLA distribution depots. DLA uses these estimates to determine expected costs and revenues at the distribution depots. Accurate workload forecasting allows DLA planners to establish appropriate surcharges for their services. Inaccurate estimates can lead to higher costs to DLA and, ultimately, to the Navy. We evaluate current Navy forecasting methods and develop several causative factors that influence issue and receipt workload. We present single and multiple regression models to predict future issue and receipt demands and compare these models with those currently used by Naval Supply Systems Command. Our results suggest that causal-based modeling is a feasible alternative to current models and may more accurately estimate future issue and receipt workload for the Navy.

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FORECASTING NAVY ISSUE AND RECEIPT WORKLOAD AT DEFENSE LOGISTICS AGENCY DEPOTS

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ABSTRACT

Each year the Defense Logistics Agency (DLA) asks the military services to estimate their future issue and receipt workload demands at DLA distribution depots. DLA uses these estimates to determine expected costs and revenues at the distribution depots. Accurate workload forecasting allows DLA planners to establish appropriate surcharges for their services. Inaccurate estimates can lead to higher costs to DLA and, ultimately, to the Navy. We evaluate current Navy forecasting methods and develop several causative factors that influence issue and receipt workload. We present single and multiple regression models to predict future issue and receipt demands and compare these models with those currently used by Naval Supply Systems Command. Our results suggest that causal-based modeling is a feasible alternative to current models and may more accurately estimate future issue and receipt workload for the Navy.

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I. INTRODUCTION

A. PURPOSE

The Defense Logistics Agency (DLA) operates several distribution depots that provide logistics support to all of the military Services. DLA charges each Service for the workload, or total demand for services at the distribution depots. Workload is comprised of three areas: 1) Issues and Receipts of items stored at the depot but managed by the individual Services; 2) storage fees for items which are owned by the service and stored at the depot; and 3) reimbursables, or charges for specific Services. Issues and Receipts of service-managed items generate the majority of total workload.

We analyze Navy workload demand at DLA distribution depots - issues of Navy managed repair parts in particular. We define issue and receipt workload as the total number of requisitions for issues, receipts, disposals and transshipments for Navy managed repairable and consumable items. We examine operational factors that might influence the demand for issues of Navy-managed repair parts, use regression analysis to understand the relationship between those factors and the number of issues. Finally, we use the causative factors to develop a regression model that predicts future workload of Navy-managed items at distribution depots.

B. THE PROBLEM

Each year the Defense Logistics Agency asks the military Services to estimate their future workload demands at DLA distribution depots. DLA uses these estimates to determine costs and revenues at the depots. Policy makers set the "price" or surcharge for services based on the expected volume of business. Distribution depot total revenue is based on the surcharge for each requisition multiplied by the number of requisitions received. As a Defense Business Operating Fund (DBOF) activity, DLA is expected to establish the surcharge for its services so that it "breaks even", showing neither profit nor loss. If the volume, or number of requisitions the distribution depots receive, is lower than the volume that they expected to receive, the distribution depots may experience a deficit.

In 1993, analysts at Naval Supply Systems Command (NAVSUP) estimated the FY 1993 total workload of Navy-managed items at DISTRIBUTION depots to be 3.9 million requisitions. DLA budget analysts projected a dramatically higher total of 6.9 million requisitions for the same period. The difference between DLA and NAVSUP estimates meant a difference in surcharge revenue expectations of $87 million dollars. DLA managers knew that inaccurate estimates would lead to understaffing at the distribution depots, resulting in slower response time to requisitions and decreased customer service, or overstaffing, resulting in increased costs. Subsequent forecasts in 1995 and 1996 showed smaller, but still significant differences in estimations. Fiscal year 1997 estimates by the two agencies differ by more than 1.2 million requisitions, or an approximate difference in expected revenue of $28 million.

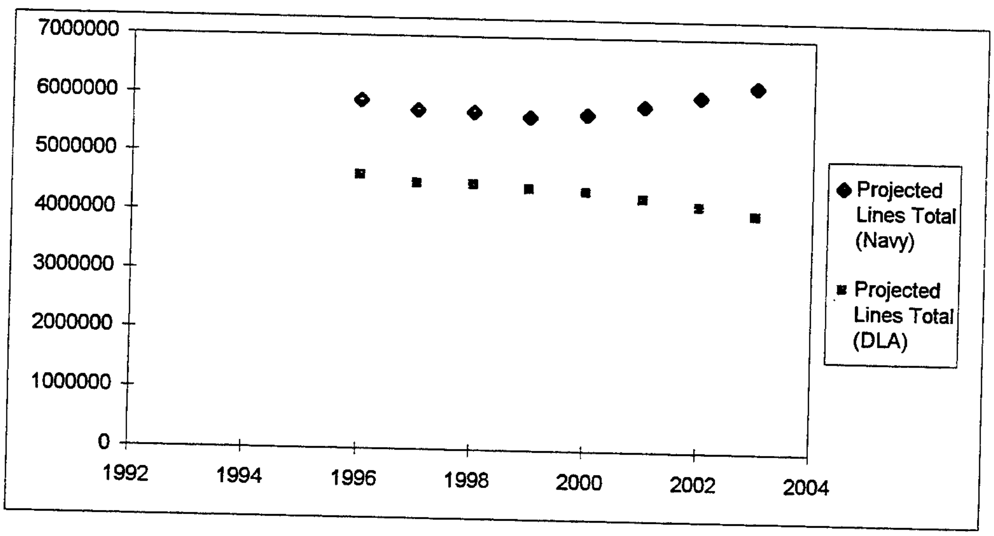


Figure 1.1. Comparison of NAVSUP and DLA forecasts from 1996 to 2003.

Figure 1.1 shows the difference between DLA and NAVSUP estimates of expected issues and receipts of Navy-managed items at DLA distribution depots for the period 1996 to 2003. Actual workload data are available for only two years in which the Navy made projections to DLA: in 1994, the Navy forecast was lower than actual workload by 445,000 line items; and in 1995, it was lower than actual workload by 923,000 line items. This translates to $12,460,000 less revenue for DLA 1994 and $25,844,000 less revenue in 1995.

1. DLA Perspective

DLA budget analysts have indicated that the higher workload estimates received from NAVSUP are inaccurate and will lead to higher operating costs at distribution depots. DLA managers establish a surcharge for requisitions so that the total revenue they expect to receive equals the total expected costs at the distribution depots. If demand is lower than expected, total revenue will be lower than total costs, and the depots will experience an operating loss. In order to recover that loss in the following year, DLA managers must establish a higher surcharge, which means higher total costs to the Services. DLA managers want the Services to provide accurate workload forecasts because they realize that their own forecasting methods are likely to be inaccurate for three reasons.

1. **DLA has only four years of historical data on issues and receipts of Navy managed items.**

   DLA began consolidation of Service depots in 1991. As DLA personnel took possession of each depot, they installed the Standard Automatic Materiel Management System (SAMMS). In 1993, DLA brought the Management Information System (MIS) online. The last depots were converted to the MIS in 1994. MIS has only two years of accurate data on demand activity at the former Navy depots. Navy databases do not have data for total issue and receipt requisitions.

2. **DLA budget analysts are not familiar with Navy operational factors that would influence workload.**

   These factors include policies, programs, acquisitions and events that are specific to the Navy, such as ship commissionings and decommissionings, station deactivation, inventory stockage policy changes, Consolidated Shipboard Allowance List (COSAL) buyout, and programs such as Direct Vendor Delivery.

3. **DLA databases classify inventory items differently.**

   The Management Information System (MIS) at DLA classifies inventory much differently than do the NAVSUP or NAVICP databases. The Management Information System classifies distribution depot workload data in categories that support a recent DLA initiative called *discrete pricing*. Discrete pricing allows DLA managers to establish different surcharges for different types of requisitions. The MIS database allows managers to distinguish total workload by item owner and depot location for several different categories, including issues and receipts of binnable,

medium bulk, heavy bulk and hazardous items. The database also displays data on transshipment and disposal requisitions. DLA's MIS system does not use Cognizance Groups (COGs) to categorize items and cannot distinguish between Navy-managed repairables and Navy-managed consumables. Cognizance Groups are unique to the Navy and are used to distinguish between the type of item and the Inventory Control Point (ICP) that manages that item.

2. Navy Perspective

NAVSUP analysts suspect that their current forecasting techniques give a reasonable estimate of future workload at the distribution depots. Although they indicate that a causal forecasting model may give more accurate predictions, given the complexity of the forecasting environment and the lack of historical data on issue, receipt and disposal requisitions, they doubt a viable alternative model can be created.

C. RESEARCH OBJECTIVES

Our research consists of three elements: (1) We will examine the model currently being used at NAVSUP to forecast issues and receipts at distribution depots. (2) We will identify possible causative factors that might be used in alternative causal-based models for predicting workload indicators. (3) We will analyze the causal-based models to determine if they more accurately predicts actual workload of Navy-managed items at distribution depots.

D. RESEARCH QUESTIONS

Our research seeks to answer two primary questions. First, can a causal-based model be used to forecast issue and receipt workload at DLA distribution depots? Second, are these forecasts more accurate than the current NAVSUP forecasts?

E. PREVIEW

In the next chapter, we provide some background on the agencies involved. We also examine some of the issues and policies which make forecasting difficult. We discuss DLA's role in the consolidation of distribution depots and the effect of Consumable Item Transfer (CIT) in forecasting models. In Chapter III, we discuss the forecasting models currently being used by Naval Supply Systems Command and by DLA. In Chapter IV, we

discuss the methodology used in formulating an alternative forecasting model, and we define the scope of the model and the assumptions used. In Chapter V, we develop and discuss the causal-based models formulated as alternatives to the current NAVSUP model. In Chapter VI we compare and contrast alternative models, summarize the thesis, and provide conclusions and recommendations.

II. BACKGROUND

Since 1960, the Department of Defense (DoD) has spent considerable effort streamlining the logistics function within the military. Prior to 1960, each service managed its own inventories, resulting in much duplication of effort. DoD took steps to create a more centralized and standardized logistics process. First, DoD removed the service's responsibility for managing consumable items procured by the General Services Administration (GSA). Instead, GSA would procure and manage these items for all of the Services. Second, DoD created the Defense Logistics Agency, charged with managing consumable items. This eliminated duplication of effort in managing consumables and provided greater standardization among Services.

A. AGENCIES INVOLVED

1. Defense Logistics Agency

As part of the Department of Defense, the Defense Logistics Agency is a combat support agency. It provides materiel and supplies to the military Services and supports their acquisition of weapons and other equipment. Support begins with joint planning with the Services for parts for new weapon systems, extends through production and service, and concludes with the disposal of materiel that is obsolete, worn out or no longer needed. DLA provides supply support, contract administration services, and technical and logistics services to all branches of the military.

2. Naval Supply Systems Command

NAVSUP directs the operation of the Navy supply system under the authority of the Secretary of the Navy. Its mission is to develop, manage and operate the Navy supply system to provide supplies and services to satisfy peacetime and wartime fleet and other customer mission requirements. NAVSUP's primary mission is to support the Naval operating forces and the maritime strategy of the United States.

3. Naval Inventory Control Points

The inventory management responsibilities of NAVSUP are implemented through Inventory Control Points (ICPs). NAVICP-Philadelphia manages aviation-related parts

and supplies. NAVICP Mechanicsburg (NAVICP-Mech) manages maritime applications. Their goals are to:

1. provide worldwide acquisition and control of weapons systems and material,
2. provide total life cycle configuration management, logistics support data, and supply support for assigned weapons systems,
3. provide inventory management for assigned secondary items, and
4. contribute to the readiness and sustainability of the fleet.

B. POLICY ISSUES

1. Depot Consolidation

In 1990, DLA began to consolidate supply depots. DLA took control of the various service depots and, in some cases, consolidated separate service depots into a single defense depot. In 1993, DLA implemented an integrated Management Information System (MIS) which consolidated requisition data from all of the distribution depots. DLA currently has about two years of historical data on all Navy related surcharges for issues, receipts, disposals and transshipments in the MIS system.

2. Consumable Item Transfer

DLA manages all of the consumables that are generic to all the Services. Consumables used by some (but not all) of the Services are managed by one "lead" service. Consumables used by only one service are managed by that service.

In 1991, DLA began the Consumable Item Transfer (CIT) of 981,000 consumable items previously managed by the Services (Baker, 1991). Over four years, in two phases, nearly all of the consumables managed by the Services were turned over to DLA. The Navy transferred more than 280,000 items in Phase I and is scheduled to transfer 40,000 items in Phase II. Phase II is scheduled to be complete in September of 1997, but the transfer is currently under a moratorium because of disagreement over how DLA should "buy" the consumable items owned by the Navy (Booker, 1996). Approximately 20,000 Phase II items have not yet been transferred. Not all consumable items used by the Navy will be transferred to DLA: some categories of consumables, such as Subsafe Level I

items and those used in the Navy's nuclear power program, will continue to be managed by the Navy. In order to exclude the effect of Consumable Item Transfer on the historical data, we will examine only repairable items when developing a model to evaluate the causative factors that influence issues of Navy-managed items.

3. Discrete Pricing

The discrete pricing methodology also allowed the depots to assign different surcharges for receipts, transshipments, and on-base or off-base issues. We were unable to obtain sufficient data to measure the effect of discrete pricing on total Navy workload costs. While DLA's discrete pricing has the potential to affect the total cost of issues and receipts to the Navy, we have assumed that the total cost of issues and receipts will not significantly change. Current DLA and NAVSUP forecasting models also assume that discrete pricing will not affect total issue and receipt workload costs.

4. Direct Vendor Delivery

Direct Vendor Delivery is a recent policy initiative that seeks to reduce workload at distribution depots by having commercial vendors ship supply items directly to the end user. While this initiative is certain to affect Navy workload in the future, it is not significant at this time because direct vendor deliveries constitute only a small portion of total issues. The future effect of Direct Vendor Delivery is worthy of further study, but is beyond the scope of this thesis.

III. CURRENT FORECASTING MODELS

A. DLA FORECASTING

DLA budget analysts do not have a formal model for estimating Navy issue and receipt workload. Typically, the analysts determine the total issue and receipt workload one or two quarters into a given year, then expand current year-to-date data to represent the entire year. They then assume that the percent change in issue and receipt workload between the current year and previous years can be applied to future years. For example, if the depots have processed three million requisitions by the end of the second quarter of the fiscal year, then they assume that the total Navy workload for that year will be around six million requisitions. This workload estimate is compared to previous periods to establish a trendline for future estimates. If this workload data is significantly different from the NAVSUP estimate for a given year, DLA analysts make a new projection for that year. Typically, DLA analysts "split the difference" between their informal estimate based on the "year-to-date" workload and the Navy's estimate for the year. For example, if the original NAVSUP estimate were eight million requisitions for the year and the DLA estimate were six million requisitions for the year, then the DLA analysts will split the difference and estimate a total of seven million requisitions for the year. DLA budget analysts then create a new forecast trendline using their adjusted estimates and project the new percentage change of estimates into future years. The forecast period is typically six years and is completed in conjunction with Program Objective Memorandum development.

B. THE NAVSUP FORECASTING MODEL

NAVSUP analysts assume that the estimated percentage change in future wholesale sales (in dollars) will also be the change in total requisitions for Navy managed issues and receipts at the distribution depots. Total sales is the total cost in dollars of all Navy-managed items issued during a given year, wholesale and retail combined. Typically, wholesale sales comprise about 30% of total sales. By assuming that the total percentage change in the cost of wholesale items is the same as the total percentage

change in the number of requisitions at the depots, NAVSUP analysts can use the same forecasting model for estimating future issues and receipts at DLA that they use for estimating future wholesale sales. NAVSUP budget analysts receive the wholesale sales forecasting estimates for maritime items from NAVICP Mechanicsburg, and the wholesale sales estimates for aviation items from NAVICP Philadelphia. NAVSUP analysts then add the estimates from Philadelphia and Mechanicsburg to create a total wholesale sales estimate. NAVICP Philadelphia and NAVICP Mechanicsburg use different models for forecasting wholesale sales for the parts they manage.

1. NAVICP Mechanicsburg Wholesale Sales Forecasts

NAVICP-Mech analysts use a simple "straight line" method for forecasting wholesale sales. This type of forecasting, called judgmental or qualitative, is appropriate when hard data is scarce or difficult to use (Levenbach and Cleary, 1984). Forecasters at NAVICP-Mech examine two primary elements of total wholesale sales, basic sales and program sales. The equation is: *Total wholesale sales = Basic sales + Program sales.*

Basic sales are current fiscal year-to-date sales, as well as historical sales. They expand current year-to-date sales data to represent the entire year. For example, if they have had sales of $20 million in the first quarter, they assume total basic sales of $80 million for the year. The forecasters also factor predicted changes, such as projected decommissionings, predicted price changes, COG migration, and the effect of consumable item transfer, into the final basic sales estimate. Forecasters make a "best guess" of the effect of these policy changes based on intuition and experience.

Program sales include COSAL buyout and other programs in which a specific customer or program sponsor has indicated that it will buy a certain number of repair parts.

Once all of the basic and program sales estimates have been added together, NAVICP-Mech estimates a percent change in wholesale sales by determining the difference in total wholesale sales from the previous year.

2. NAVICP Philadelphia Wholesale Sales Forecasts

NAVICP Philadelphia uses a spreadsheet model entitled Statement 5A to estimate future wholesale sales. The spreadsheet model is complex and accounts for all expected future sales. Prior year net sales form the baseline for the model. Several elements are then either added or subtracted from the baseline number to form a new estimate. These elements are summarized below.

1. Prior-Period Unfilled Customer Orders: the total value of requisitions received (but not yet satisfied) from the previous year which will result in a sale when satisfied.

2. Prior Period Net Sales: actual net sales for the current fiscal year to date. A "strength factor" is used as an expansion factor to convert partial-year sales into a full-year projection.

3. Non-Recurring Customer Orders/Net Sales: "one time only" sales from the previous year which are not expected to be seen in future years. Non-Recurring Customer Orders and sales are subtracted from prior-period net sales. These items include:

    a) Outgoing Cognizance Transfer: total amount of sales which occurred before the transfer date.

    b) Sales to Foreign Governments: sales to foreign governments which are not expected to reoccur.

    c) Provisioning: total sales for initial provisionings.

    d) Other: any other sales which are considered non-recurring in nature. These sales are typically identified as Non-Recurring Demand (NRD) items and Follow-On Outfitting (FOO) items.

4. Incoming Cognizance Transfer Customer Orders/Sales: the value of estimated prior-year sales for items being transferred, prorated through the transfer date to the extent not included in the sales shown as Prior-Period Net Sales.

5. Projected Special Customer Orders/Sales: expected sales which have not occurred in the past.

Once the elements listed above have been added or subtracted from the baseline value, the model looks like this:

Prior period net sales + Prior Period Unfilled Customer Orders - Non-recurring orders + Incoming Cognizance Transfer - Outgoing Cognizance Transfer + Projected Special Customer Orders = expected net sales

Once analysts have calculated the expected net sales for a given period, they must adjust for inflation and price changes. To do this, NAVICP Philadelphia analysts multiply the expected net sales by a factor called the Net Price Change Impact (NPCI). The NPCI is calculated as follows: Difference in navy surcharge for item issue + difference in DLA surcharge for item issue + the price escalation experienced from the prior year = net price change. This net price change is calculated as a price change percentage and multiplied by the expected net sales to create the expected total wholesale sales. The Net Price Change Impact allows NAVICP analysts to adjust expected sales for inflation or deflation in prices. Once adjusted, the total adjusted expected sales represent expected total wholesale sales at NAVICP Philadelphia for the projected years.

C. NAVSUP WHOLESALE SALES PROJECTIONS

Once NAVSUP analysts receive the individual projections for wholesale sales from each of the NAVICP's, they simply sum the two projections to receive a total wholesale sales projection for the Navy. When DLA requests projected workload figures, NAVSUP analysts send DLA the projected change in wholesale sales expressed as a *percentage change* of *wholesale sales* (in dollars). This data may be ambiguous because DLA analysts express their estimates as *percentage change of requisitions* (numbers of issues, receipts, disposals and transshipments).

IV. METHODOLOGY

A. CAUSAL-BASED MODELING

Causal-based models allow the forecaster to estimate the value of one variable based on its relationship to one or more other variables (Wheelwright and Makridakis, 1985). The most common technique in causal-based modeling is regression analysis. Simple regression assumes that the functional relationship between two variables can be represented as a straight line

$$Y = \alpha + \beta X + \varepsilon_i,$$

where α is the point at which the straight line intersects the Y axis, Y is the dependent variable, β is the regression coefficient, and ε_i is the residual error. Non-linear relationships can be made linear through the use of logarithmic, polynomial or other transformations (Levenbach and Cleary, 1984). Simple regression uses the least squares method to find the equation for a straight line which has the "best fit" or most closely approximates the historical observations.

Sometimes a better model can be developed using more than one independent variable. The methodology is identical to the simple regression model except that the model uses the least squares method to fit a plane rather than a straight line,

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_m X_m + \varepsilon_i,$$

where β_m is the coefficient of the independent variable X_m (Liao, 1996). We will evaluate both single and multiple regression models in this thesis.

B. ASSUMPTIONS INHERENT IN MULTIPLE REGRESSION ANALYSIS

Four basic assumptions are integral to any multiple regression analysis. Each of the necessary conditions for these assumptions must be met before a regression equation may be considered valid (Wheelwright and Makridakis, 1985).

1. Linearity

The first assumption in the application of regression analysis is that a linear relationship exists between the dependent variable and each of the independent variables.

If the relationship is curvilinear, it may be transformed into a linear relationship through the use of data transformation.

2. Homoscedasticity

The second basic assumption is that the variance of the regression errors is constant. These errors, also known as residuals, must remain constant over the entire range of values for the independent variable. Variables with non-constant variances can give significance tests that are meaningless (Wheelwright and Makridakis, 1985).

3. Independence of Residuals

The third assumption in regression analysis is that the errors or residuals are independent of one another. This means that any given residual value is independent of the values coming before or after it. If the residuals are not serially independent, autocorrelation exists. The best way of determining autocorrelation is to compute a Durbin-Watson (D-W) statistic. This calculation can be performed by most statistical software packages such as Minitab.

4. The Problem of Multicollinearity

The last assumption integral to the use of multiple regression is the problem of Multicollinearity. Multicollinearity exists when two or more of the independent variables are highly correlated. We will develop a matrix of simple correlation's between independent variables to determine multicollinearity.

C. FORMATION OF A CAUSAL-BASED MODEL

Wheelwright and Makridakis (1985) outline a number of steps in applying multiple regression analysis.

1. Formulation of the Problem
2. Choice of Relevant Indicators
3. Initial Test Run of Multiple Regression
4. Deciding among Individual Regressions
5. Checking the Validity of the Regression Assumptions
6. Preparing a Forecast

This chapter will discuss the first two steps in the regression analysis process: Formulation of the Problem and Choice of Relevant Indicators. We will examine the data sets available and the nature of the relationship between the dependent and independent variables used.

D. FORMULATION OF THE PROBLEM

The defense logistics environment has changed radically in the last several years. Policy changes have altered the way in which repairable and consumable items are delivered to the fleet. Two major policy changes, Depot Consolidation and Consumable Item Transfer, have had a significant impact on the Navy's management of the logistics process. Additionally, the size of the Navy has decreased dramatically in real terms in the last few years. We cannot reasonably assume that the Navy's cost of supplying the fleet will either remain the same or follow historical trends.

Causal models do not rely on trends over time. Instead, they describe the nature of the relationship between two or more variables (Liao, 1996). The standard regression model attempts to describe or estimate the dependent variable in terms of one or more independent or explanatory variables.

This thesis will develop causal models to explain two dependent variables. First, we will develop a causal model to estimate the number of future issues of Navy-managed repairable items. Second, we will develop a causal model to estimate total Navy issue and receipt workload at the distribution depots.

E. CHOICE OF RELEVANT INDICATORS

Causal models are based on the relationship between the variable being predicted, known as the dependent variable, and independent variables which influence the dependent variable. Not all independent variables are suitable for use in a regression equation. Suitability of independent variables is based on the availability of data for historical periods, as well as accurate estimates of future periods for which the forecast is being prepared (Wheelwright and Makridakis, 1985). All dependent variables used and their sources are listed in Appendix A. Not all of the independent variables which we examined were useful in improving a regression equation. We examined four different data sets and

selected two of the data sets for use in our regression models. The data sets we examined are listed below.

1. Dependent Variables

a. Total Demand for Repairables at NAVICP Mechanicsburg

We extracted demand data from a NAVICP-Mech. database of 139,491 repair parts representing all repair parts having experienced demand within the last forty quarters. This data set gives total demand for non-aviation repair parts. These data do not reflect the actual number of *issues* for the repair parts; rather, they reflect the actual *number of items issued.* We assume that total number of items issued will closely approximate the total number of issue requisitions, because repair parts are typically ordered in quantities of one. This data set was useful because it was comprised of only repair parts and, therefore, was not affected by the Consumable Item Transfer. The primary disadvantage of this data set was that it covered a period of only ten years.

b. Total Issues of "7 COG" Repairables

We manually extracted the total issues of Navy-managed repair parts (issues) from NAVSUP PUB 295 for the years 1975-1995. Published annually by NAVSUP, PUB 295 is a compilation of monthly reports sent from Navy Fleet Industrial Support Centers (FISCs) to NAVSUP. This data set was particularly useful because it was the only available data set which reflected *number of issues* of repair parts rather than *number of repair parts issued.* This distinction is important because DLA charges the Navy for the number of requisitions (issues), not the number of items issued. For the purpose of this study, only "7 COG" items were analyzed. Specific descriptions for each of the Cognizance Symbols used in this analysis are listed in Appendix B. Generally, the 7 COG items refer to Navy-managed repairables. We selected repairables for analysis because they were not affected by the Consumable Item Transfer. We selected the NAVSUP PUB 295, 7-COG issue data set as the primary data for our dependent variable.

c. Total Workload for Navy-Managed Items.

We manually extracted workload data for the years 1993-1996 from workload reconciliation reports sent to the Comptroller at Naval Supply Systems

Command from the Program Budget Division at DLA. We define workload as the total number of requisitions for issues, receipts, disposals and transshipments for Navy managed repairable and consumable items. These documents are used to bill the Navy for workload at the distribution depots. The data set is listed in Appendix A. Although this data covered only four years, this was the only one that utilized actual billing data.

d. *Total Demand for Repairable and Consumable Items at NAVICP Mechanicsburg and NAVICP Philadelphia.*

The final data set for the dependent variable that we examined was extracted from the NAVICP computer database. We extracted data from computer printouts of total items demanded at NAVICP Mech and NAVICP Philadelphia. This data set included total demand for both Navy-managed repairable (7 COG) items and Navy-managed consumables. Although the data were given in terms of total number of items demanded rather than total number of requisitions, they were beneficial in examining the relationship between the demand for aviation-related items and maritime-related items.

2. Independent Variables

After analyzing fourteen possible causal variables, we selected six operational tempo (OPTEMPO) indicators for use as independent variables. Sources for the OPTEMPO data are listed in Appendix A. Some of the operations activity data dated back as far as 1973, while other data sets extended back only eight years. After analyzing all of the possible data sets, we excluded some of the data sets from the study for the following reasons:

- Historical or projected data were not easily available, making them unacceptable for a practical model. Regression analysis requires that the forecaster have both a history of data and the ability to develop reliable forecasts for dependent variables.
- Data were not reliable. Some of the data set totals were significantly different from other data set totals. When we could not verify the accuracy of the data set, we discarded that data.
- There appeared to be no significant relationship between dependent and independent variables. Initial correlation analysis on some of the data sets showed that the independent variable did not influence the dependent

variable. These dependent variables were unlikely to contribute to a good regression model.

a. Operations and Maintenance, Navy (O&M,N) Budget Data

We manually extracted Operations and Maintenance (O&M) budget data for the years 1975-1995 from Federal Budget reports. O&M funds are used for a wide variety of purposes, including supplies and materials, contracts, and civilian personnel payrolls. We selected O&M data for consideration as an independent variable because they were readily available, and because future O&M budgets are forecast in the Navy's Future Years Defense Plan. We adjusted the O&M data to 1975 constant dollars using the Consumer Price Index. We used a scatter plot and an Excel correlation analysis tool to determine if DLA issues and O&M moved together and could be expressed as a linear function. Simple correlation of 0.87 indicates that there is a relationship between the two variables.

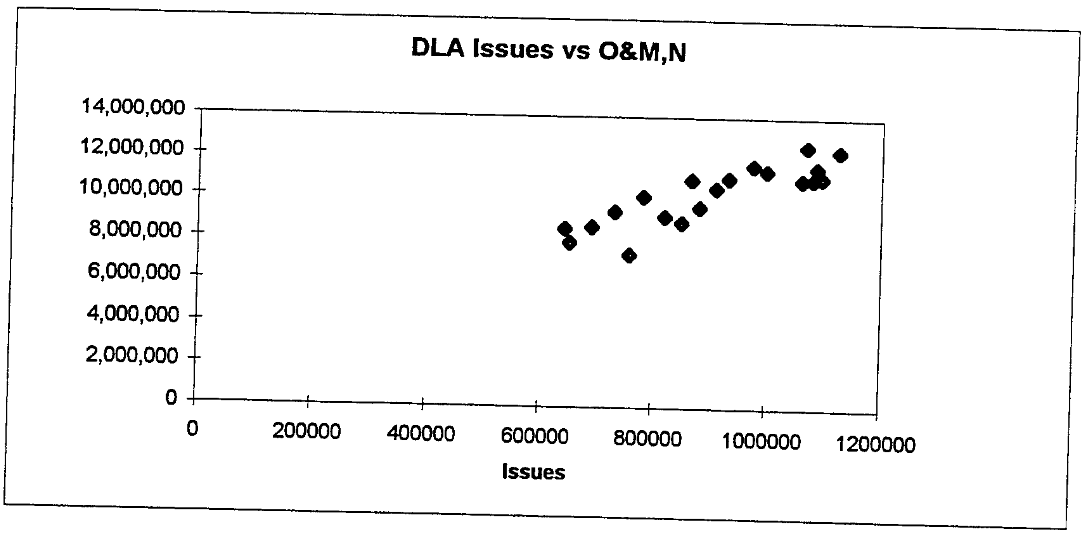


Figure 4.1. Scatter Plot Of DLA Issues Of Navy-Managed Repair Parts Vs. O&M Budget.

The scatter plot of O&M and DLA issues of Navy-managed repair parts shows that there appears to be a positive relationship between the two variables, and the relationship appears to be linear. One problem with using Operations and Maintenance was that it had the possibility of introducing multicollinearity into the regression equation.

This means that O&M data were likely to influence other independent variables as well as the dependent variable (issues).

b. Personnel End Strength (Perstrength)

We manually extracted Personnel End Strength data from Navy Budget Exhibits for the years 1975-1995. Personnel End Strength (Perstrength) is the total number of active duty officers and enlisted members in the US Navy at the end of the fiscal year. The correlation coefficient between issues and Perstrength is 0.71, indicating a possible relationship between repair part issues and active duty end strength.

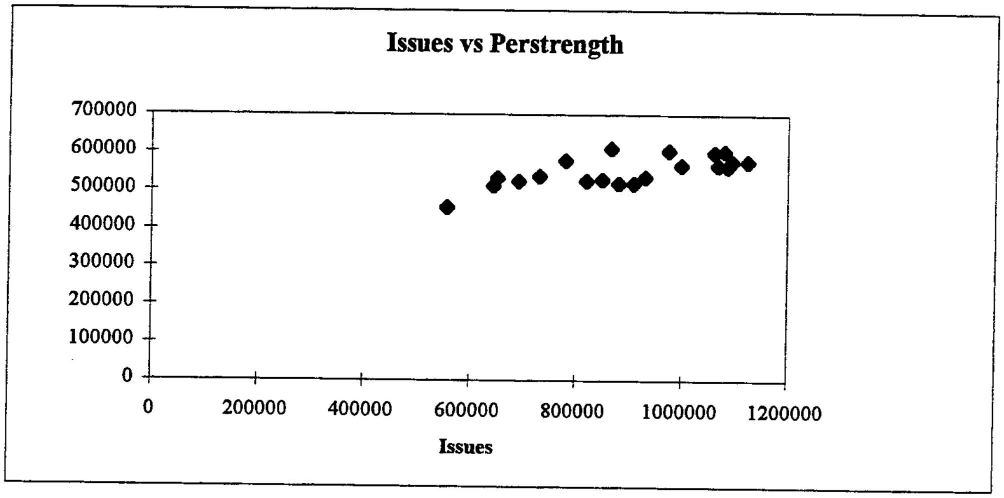


Figure 4.2. Scatter Plot Of DLA Issues Of Navy Managed Repair Parts and Active Duty End Strength (Perstrength)

c. Flying Hours

We received flying hours data from the Flying Hours Office in the Comptrollers Office, Secretary of the Navy. Flying hours data extend back to 1983 and projections are made to 1999. There is a strong correlation between flying hours and demand for repair parts at NAVICP Philadelphia because Philadelphia manages all aviation-related repair parts. As expected, there is a lesser correlation between flying hours and total issues because issues data include demand for both aviation and non-aviation related repair parts.

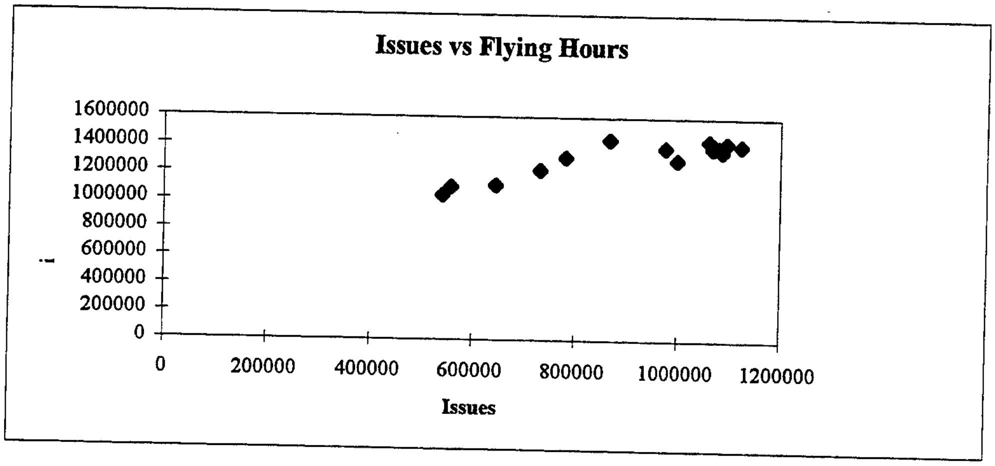


Figure 4.3. Scatter Plot Of DLA Issues of Navy Managed Repair Parts and Navy Flying Hours

d. OPTEMPO

OPTEMPO is an indicator of activity of ships, given as an average percentage of time underway for deployed and non-deployed ships. OPTEMPO by itself does not show a good relation to issues. However, when we multiplied OPTEMPO by the number of ships each year, we got a better relationship. We call the new variable of OPTEMPO multiplied by total number of ships "Total OPTEMPO." We developed two Total OPTEMPO indicators for study: Total OPTEMPO for deployed ships, and Total OPTEMPO for non-deployed ships.

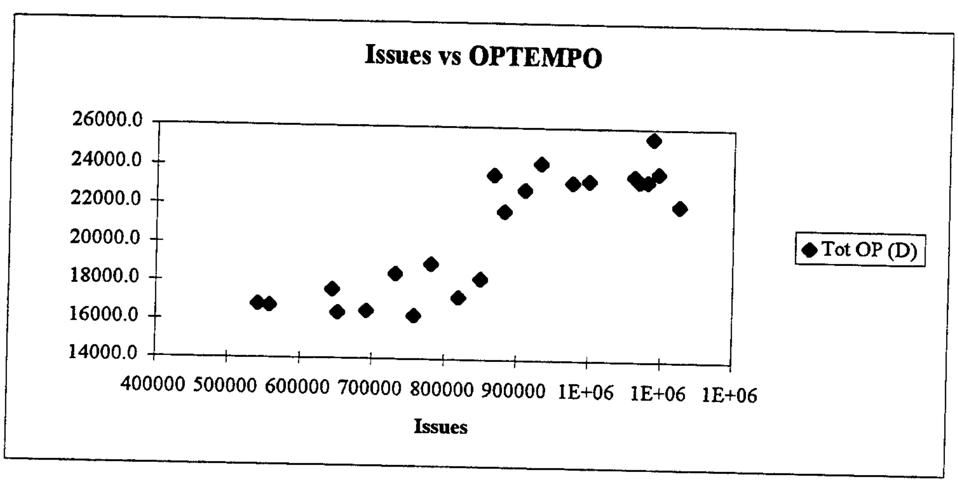


Figure 4.4. Scatter Plot Of DLA Issues of Navy Managed Repair Parts and Total OPTEMPO For Deployed Ships

e. Steaming Hours

Steaming Hours data were available only for the years 1986 - 1993 and did not have a significant correlation to issues. We excluded steaming hours from further study.

F. SUMMARY

In this chapter, we presented the basic regression model and outlined the necessary assumptions for any regression model. We also explained the process for developing a causal model and performed the first two steps in developing our own regression model: formulation of the problem and choice of relevant indicators. Chapter V will develop the next four steps in developing our regression model.

V. ANALYSIS

Chapter IV discussed the first two steps in formulating a regression model. This Chapter will discuss the next four steps in the process.

1. Initial Test Run of Regressions
2. Deciding among Individual Regressions
3. Checking the Validity of the Regression Assumptions
4. Preparing a Forecast

A. INITIAL TEST RUN OF REGRESSIONS

The initial test run of multiple regressions allowed us to include all of the dependent and independent variables. We examined several regressions and decided that we would first select issues of Navy-managed repair parts (hereafter called issues) as the dependent variable. Once we had developed a regression model to forecast issues, we would develop a second regression model using total workload as the dependent variable. The regression process outlined in the previous paragraph would allow us to discover which independent variable had the greatest influence on the dependent variables we selected. We started by developing several plausible regression equations using issues as the dependent variable and several different combinations of independent variables.

At this stage of the regression analysis process, we were primarily interested in discovering which independent variables best explained changes in the dependent variable. We first examined the coefficient of determination (r^2). For example, if the r^2 of a given model is .84, it means that 84% of the sample variation from the mean of the dependent variable can be explained by the change in the independent variable.

The results of the initial regression test runs are listed below. A graph of the residuals or error terms (ε_I) from each model in Appendix C. The residuals are necessary to critique the validity of the regression model. Ideally, the error terms will appear to be distributed randomly.

1. Issues vs. OPTEMPO (Deployed and Non-Deployed) and Flying Hours

The first model we developed utilized issues as the dependent variable. The model contained total OPTEMPO for both deployed and non-deployed ships and flying hours as independent variables. The number of observations was limited to 13 because flying hours data were available only from 1983. The coefficient of determination (r^2) was .81.

Table 5.1. Regression Data for Issues Using OPTEMPO and Flying Hours

Predictor	**t-Ratio**
OPTEMPO (Deployed)	1.05
OPTEMPO (Non-Deployed)	.96
Flying Hours	.32
r^2(adj)	**.81**
F-Ratio	18

2. Issues vs. OPTEMPO, O&M, Navy, and Flying Hours

Our next model utilized issues as the dependent variable and introduced Operations and Maintenance data into the model. Again, the number of observation was limited to 13 years because flying hours data have been recorded only from 1983 to present. An r^2 of .84 was better than the previous model's.

Table 5.2. Multiple Regression Data for Issues

Predictor	**t-Ratio**
OPTEMPO (Deployed)	.827
OPTEMPO (Non-Deployed)	.467
O&M, Navy (adjusted)	1.69
Flying Hours	-.033
r^2(adj)	**.84**
F-Ratio	15.54

We also conducted single regression analysis using total issues of repair parts as the dependent variable. In each of these models, we utilized only one independent variable.

3. Issues vs. Operations and Maintenance, Navy

This model examined the relationship between issues and the O&M budget over a twenty year period. The r^2 value of .77 was lower than the r^2 of the multiple regression models listed above.

Table 5.3. Regression Data for Issues Using O&M.

Predictor	**t-Ratio**
O&M, Navy (adjusted)	8.30
r^2(adj)	.772
F-Ratio	68.87

4. Issues vs. Flying Hours

Although we developed this model, we believed that it would not be the best single regression model because there is no reason to believe that flying hours of Navy aircraft would have a significant influence on the number of issues of non-aviation related parts. An r^2 .755 was lower than that of most of the other models.

Table 5.4. Regression Data for Issues Using Flying Hours

Predictor	**t-Ratio**
Flying Hours	5.91
r^2(adj)	.755
F-Ratio	34.91

5. Issues vs. Perstrength

This model examined the relationship between issues and active duty personnel end-strength. The r^2 of .48 was the lowest of the regression models we developed.

Table 5.5. Regression Data for Issues Using Perstrength

Predictor	**t-Ratio**
Perstrength	4.22
r^2(adj)	**.484**
F-Ratio	17.85%

6. Issues vs. Total OPTEMPO (Deployed and Non-Deployed)

This model evaluated the relationship between issues and OPTEMPO for both deployed and non-deployed ships over twenty years. The coefficient of determination (r^2) of .82 suggested a relatively strong relationship between issues and OPTEMPO.

Table 5.6. Regression Data for Issues Using OPTEMPO

Predictor	**t-Ratio**
OPTEMPO (Deployed)	1.10
OPTEMPO (Non-Deployed)	3.27
r^2(adj)	**.82**
F-Ratio	47.32

B. DECIDING AMONG INDIVIDUAL REGRESSIONS

Once we had completed an initial test run of regressions, we were able to eliminate independent variables which did not appear to significantly explain the dependent variable. In this case, we eliminated steaming hours and Perstrength from further models. We utilized the stepwise technique to select the best possible multiple regression model.

1. Stepwise Technique

The stepwise technique starts by selecting the independent variable that best explains the variation in the dependent variable. By using the residuals from the first regression, a second variable is found that best explains the remaining variation in the dependent variable. The model is then re-estimated with the new variable included. The calculations and selection procedure are repeated until no remaining variable significantly

improves the equation. At each step, the variables are examined with a partial F test to determine if any of the previously selected independent variables are not now contributing significantly (Levenbach and Cleary, 1984). Using the stepwise technique, we selected two independent variables, Operations and Maintenance and Deployed OPTEMPO, as the best combination of independent variables for use in the regression equation. When we regressed only these variables, we received the following results.

Table 5.7. Regression Data for Issues Using OPTEMPO and O&M

Predictor	**t-Ratio**
O&M, Navy	2.76
OPTEMPO (Deployed)	2.19
r^2(adj)	**.873**
F-Ratio	42.39

The regression equation is:

Issues = -509514 + .0743 O&M, Navy + 29.5 Deployed OPTEMPO

The coefficient of determination, (r^2) of .873 indicates that 87.3% of the total variation is explained by a straight line representing the regression equation. This r^2 is higher than any of regressions made in the initial test runs of single or multiple regressions. The combination of O&M, Navy and Total Deployed OPTEMPO gives the best "fit" of any of the independent variables we have examined.

C. CHECKING THE VALIDITY OF THE REGRESSION ASSUMPTIONS

Once a regression equation was selected, we needed to check the validity of the regression assumptions outlined in Chapter IV. No matter how high the r^2 of a regression model is, it is not valid if the model does not meet these assumptions. Although we examined several independent variables, not all of these causal variables met the required assumptions. When we regressed all independent variables against the dependent variable (issues), none of the independent variables had a t-statistic significantly close to an absolute value of two. The t-statistic measures the statistical significance of the regression

coefficient for an independent variable. The t-distribution is shorter and fatter than a normal distribution curve, but becomes more like the normal distribution curve as the sample size becomes larger. When the sample size n = 30, the observed t-value should have an absolute value of greater than two for significance at the 95% confidence level (Levenbach and Cleary, 1984). While all of the independent variables were significant in single regressions against issues, the t-statistics for all of the independent variables in many of the initial multiple regressions were unacceptable. The goal is to select those variables which improve the regression equation while discarding those variables which do not significantly improve the equation.

1. Studying The Matrix of Simple Correlations

Before we selected a multiple regression model, we needed to develop a matrix of simple correlations. The matrix allowed us to identify independent variables that were highly correlated. High correlation between independent variables indicates multicollinearity and degrades the regression model.

	OPTEMPO (D)	**OPTEMPO (N)**	**#Ships**	**flying hours**
OPTEMPO (N)	0.946			
# Ships	0.944	0.955		
flyhours	0.791	0.849	0.830	
OandM	0.785	0.820	0.838	0.801

We observed relatively high simple correlations between all of the independent variables. Wheelwright and Makridakis state that the forecaster should become cautious when simple correlations exceed values from 0.8 to 0.9. When the simple correlation between two independent variables was greater than .8, we eliminated them from the same multiple regression model. The model that we selected used O&M and OPTEMPO as independent variables. The simple correlation of .78 between the two variables indicated possible multicollinearity, but was not significant enough to invalidate the model. One way to avoid the problem of multicollinearity is to use only one independent variable in each model, i.e., single regression. The table below summarizes the results of regressing

each of the independent variables separately. Although both of the models were acceptable, the coefficients of determination in these models were lower than in the multiple regression model that combined both of the variables.

Table 5.8. Single Regressions for Issue and Receipt Workload

Predictor	OPTEMPO	O&M
r^2(adj)	**.742**	**.772**
t-Ratio	7.84	8.3
F-Ratio	61.43	68.87

2. Tests of Significance

The F-statistic provides an overall test of significance for the entire model. To express the significance of the coefficient of determination (r^2), the F-statistic compares the explained and unexplained variance as a ratio. As the sample size (n) gets larger, the necessary value of the F-statistic required gets smaller. Wheelwright and Makridakis use the following table for determination of significance of the F-statistic.

Table 5.9. F-statistics Table of Significance

Confidence Level	Number of Observations	Value of the F-Statistic Required for Significance
95%	6 to 10	6 or greater
	10 to 45	5 or greater
99%	6 to 10	14 or greater
	10 to 45	10 or greater

The regression equation we selected has an F-statistic of 42.39, well above the required value for significance at the 99% confidence level. This indicates that the regression equation is valid for forecasting purposes. Our next step, is to prepare a forecast.

D. PREPARING A FORECAST

In order to create a causal based forecast, we must be able to estimate the future values for each of the independent variables used in the equation. The two independent variables with the greatest causal effect on issues were Operations and Maintenance dollars and total OPTEMPO for deployed ships. Each of these variables is discussed in Chapter IV, and the sources for the historical data and future estimates are listed in Appendix A. We developed forecasts for the years 1993 to 1998, allowing us to forecast for known values (1993-1996) as well as future, unknown values (1997-1998). The results are summarized below.

Table 5.10. Forecast Of Issues And Receipts Workload From 1993 - 1999

Year	Estimate	Actual	Percent Difference
1993	726843	731725	.67%
1994	640064	644220	.65%
1995	566240	557929	1.47%
1996	541152	542019	1.60%
1997	479566		
1998	447402		
1999	427108		

The small difference between our estimates and the actual number of issues from 1993 to 1995 suggests that the regression equation that we developed accurately predicts future issues of Navy-managed repair parts.

After developing a model to predict issues of Navy-managed repair parts we used the same procedures to develop a model to predict total issue and receipt workload. Total issue and receipt workload data included issues, receipts, disposals and transshipments of all Navy managed items. The primary disadvantage of using the workload data sets was that they included only four years of data (1993-1996). After performing an initial test run of possible regressions and utilizing the stepwise technique to select the best combination

of independent variables, we found that O&M and OPTEMPO for deployed provided the highest R^2

Table 5.11. Regression Results for Issue and Receipt Workload

Predictor	**t-Ratio**
O&M	38.69
OPTEMPO (deployed)	-24.23
R^2(adj)	.999
F-Ratio	3771.6

The extremely high value of R^2 can be partially explained by the low number of observations (n=4). There are only four years of data because the billing reports from which the data sets were taken have only been used for four years. The regression equation is:

Workload = 39694.2 + (2.282 * O&M) + (-2673.25 * OPTEMPO)

We improved the significance of the model by eliminating the OPTEMPO variable. The single regression improved the model's degree of freedom from one to two. The r^2 is still good at .91 and the t-statistic and F-ratio are also acceptable.

Table 5.12. Regression Results for Issue and Receipt Workload

Predictor	**O&M**
r^2(adj)	**.91**
t-Ratio	5.6
F-Ratio	31.37

The regression equation is:

Workload = -7245088+ (1.62597* O&M)

We used this regression equation to predict future workload for Navy-managed items at DLA depots, developing forecasts for the years 1996 to 1999. This allowed us to

forecast for a known value (1996) as well as future, unknown values (1997-1999). We then charted both the actual values and our regression-based estimates against the estimates provided by analysts at NAVSUP and DLA. While the NAVSUP estimates were more accurate than the DLA estimates for 1994 and 1995, the DLA estimates were more accurate for 1996. Our regression based forecast is slightly higher than the DLA forecast for 1996 and slightly lower than the DLA estimates in 1997 through 1999. Our 1996 estimate was more accurate than the estimates of either DLA or NAVSUP.

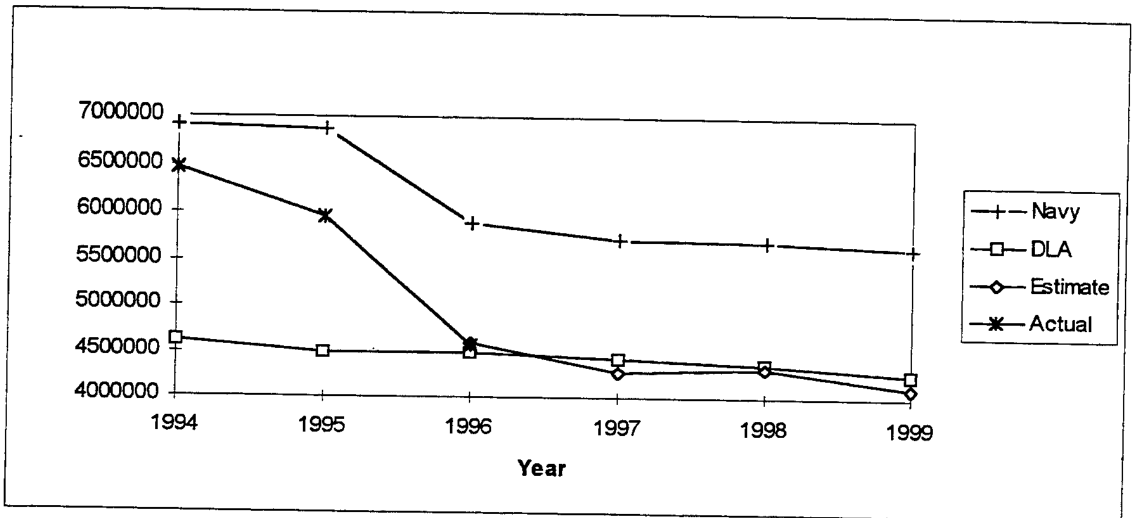


Figure 5.1. Comparison of Issue and Receipt Workload Forecasts

VI. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

A. SUMMARY

In this thesis, we addressed the need for an accurate method of forecasting future Navy workload at Defense Logistics Agency (DLA) distribution depots. We examined the different perspectives of DLA and Naval Supply System Command (NAVSUP) with regard to the forecasting problem. In Chapter II, we discussed the background of the agencies involved in the forecasting process, as well as policy issues that affect the workload demand at the depots. In Chapter III, we examined the models that NAVSUP and DLA currently use to forecast workload demand. In Chapter IV, we developed a methodology for our model formulation and adopted a six-step process for applying regression-based analysis to the forecasting problem. Finally, in Chapter V, we developed both single and multiple regression models to forecast both issues of Navy-managed repair parts and Navy issue and receipt workload. We then compared our workload model against the workload models used by NAVSUP and DLA.

B. CONCLUSIONS

We asked two primary research questions in this thesis: First, can a causal-based model be used to forecast issue and receipt workload at DLA distribution depots? Second, are these forecasts more accurate than the current NAVSUP forecasts?

We identified two causal factors as significant influences on Navy issue and receipt workload: Operations and Maintenance budget for the Navy and the total operating tempo for deployed ships (OPTEMPO (D)). We created the OPTEMPO (D) variable by multiplying the total number of battle force ships by the OPTEMPO for deployed ships.

We conclude that a causal based model is a feasible alternative to the current NAVSUP model. The first model that we developed showed that O&M and OPTEMPO were strongly correlated to issues of Navy managed repair parts. We used the model to predict issues for the years 1993 to 1996. Our predictions were within two percent of the actual value in each of the years forecasted. Our second model showed that O&M and OPTEMPO are also strongly correlated to issue and receipt workload.

We also conclude that when our regression model was used to predict issue and receipt workload, it was more accurate than the NAVSUP model at predicting known values. While the regression model we developed for issue and receipt workload appears to be accurate, we note that it is based on only four years of observations.

C. RECOMMENDATIONS

We recommend that a causal based model be used in conjunction with the current NAVSUP model to forecast Navy workload. Although our model appears to more accurately predict issue and receipt workload, intuition and personal experience will be necessary to estimate the effect of policy changes on workload. We also recommend that workload projections be made for the total number of requisitions for issues, receipts, disposals and transshipments of Navy-managed items, rather than as a single percentage change of wholesale sales. As each year's workload data become available, it should be added to the database, and a new regression model should be developed.

Additional studies should seek to determine the effect of various policy initiatives on Navy issue and receipt workload. Also, NAVSUP should develop a method for forecasting expected costs for storage and reimbursables at the distribution depots.

APPENDIX A. ANNUAL DATA FOR VARIABLES

(1)	(2)	(3)	(4)	(5)	(6)	(7)
1975	758300	382	42.5	26.5	16235	10123
1976	652396	368	44.5	25	16376	9200
1977	692152	366	45	27.5	16470	10065
1978	819833	371	46.4	29.1	17214.4	10796.1
1979	849559	378	48.1	27.8	18181.8	10508.4
1980	881211	384	56.5	28.9	21696	11097.6
1981	909724	397	57.5	28.5	22827.5	11314.5
1982	931758	420	57.6	29	24192	12180
1983	998961	420	55.5	27	23310	11340
1984	1087007	425	60	28	25500	11900
1985	1068230	435	53.6	27.4	23316	11919
1986	1124945	437	50.5	26.9	22068.5	11755.3
1987	1095384	446	53.2	27	23727.2	12042
1988	1080271	437	53.3	26.5	23292.1	11580.5
1989	1061179	434	54.3	28.5	23566.2	12369
1990	975557	416	55.8	28.7	23212.8	11939.2
1991	866419	400	58.9	29.6	23560	11840
1992	781363	356	53.2	29.2	18939.2	10395.2
1993	731725	342	53.9	28.4	18433.8	9712.8
1994	644220	315	55.8	31.5	17577	9922.5
1995	557929	302	55.4	28.2	16730.8	8516.4
1996	542019	300	56	28.9	16800	8670
1997		297	55.3	28	16424.1	8316
1998		295	55.5	28	16372.5	8260
1999		296	55.5	28	16428	8288

Column Description and source of data:

(1) Year
(2) Issues of 7-COG items - NAVSUP PUB 295
(3) Number of battle force ships - FY 1997 Budget Estimates, (Number of Ships)
(4) OPTEMPO (D) OPTEMPO for deployed ships. - FMB-123 Comptrollers Office, Department of the Navy.
(5) OPTEMPO (ND): OPTEMPO for non-deployed ships - FMB-123 Comptrollers Office, Department of the Navy.
(6) Total OPTEMPO (D) - Column 3 * OPTEMPO (D)
(7) Total OPTEMPO (ND) - Column 3 * OPTEMPO (ND)

(8)	(9)	(10)	(11)	(12)	(13)
1975	N/A		7297225	54	7297225
1976	N/A	531801	8299800	57	7847614.06
1977	N/A	523407	9689813	61	8602507.25
1978	N/A	524883	11065506	65	9130739.61
1979	N/A	527475	11935515	73	8844775.58
1980	N/A	517227	14667737	82	9576750.61
1981	N/A	517227	17742999	91	10501356.9
1982	N/A	534773	19728489	97	10998888.2
1983	1299050	565576	21070587	100	11381501.8
1984	1359745	563198	22265628	104	11529266.5
1985	1385464	566101	25130941	108	12565470.5
1986	1404864	576775	25162760	110	12351792.8
1987	1422037	576775	23346965	114	11056925.3
1988	1391249	603515	24135975	118	10976462
1989	1434865	599957	25233432	124	10948053.6
1990	1385346	604299	28224712	131	11618129.3
1991	1439760	609410	27626000	136	10912472.8
1992	1309203	577565	26237262	140	10061045.6
1993	1218522	536836	25035384	145	9321132.59
1994	1108179	511911	23396200	148	8493357.35
1995	1096688	454105	22196400	152	7835737.01
1996	1035576		21676333	156	7475555.87
1997			20196200	160	6790972.25
1998			21358600	165	6964198.06
1999			21327400	172	6671012.33

Column Description and source of data:

(8) Year
(9) Flying Hours - Flying Hours Program Office
(10) Perstrength: Active Duty End Strength - Jane's Fighting Ships
(11) O&M, N Operations and Maintenance, Navy: Navy Program Objective Memorandum, and Federal Budget of the United States Government.
(12) CPI: Consumer Price Index - Consumer Price Index Detailed Report.
(13) O&M,N (adjusted): Column 11 adjusted using Column 12.

APPENDIX B. NAVY MANAGED REPAIR PART ISSUES

Table 1. Issues of Navy-managed repair parts by Cognizance Group (COG) for 1975-1985

COG	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985
7E							1299	3778	3426	3080	3642
7G							29593	73381	76368	86040	94322
7H							48533	124642	144123	157647	189700
4A	4204	1064	2061	1875	2190	2280	1507				
6E	976	896	1164	1111	935	904	370				
4G	53734	52738	61376	63099	68213	65985	34709				
6G	6872	6120	3624	4116	4142	4711	4261				
2H	40024	40518	40571	39556	42338	46295	26409				
4N	38990	41698	45416	47313	50883	47510	25234				
2R	598268	496112	523150	646176	664942	700000	730833	726575	769391	832815	406724
4U	12269	10397	11699	14009	13404	11565	5892				
6U	2963	2853	3091	2578	2512	1961	1084				
7N											5
7R											366133
7Z								3382	5653	7425	7704
Total	758300	652396	692152	819833	849559	881211	909724	931758	998961	1087007	1068230

Table 2. Issues of Navy-managed repair parts by Cognizance Group (COG) for 1986-1995

COG	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
7E	4765	3838	11580	11796	10323	10025	8277	7946	7838	6853
7G	105784	100660	72646	68404	63992	57448	47353	41302	32954	27356
7H	231298	236290	260665	235229	218677	195272	176788	151194	122076	104437
4A										
6E										
4G										
6G										
2H										
4N										
2R										
4U										
6U										
7N	18	62	44	50	11	18	5	1	2	0
7R	774713	746528	726123	738004	676448	598370	543410	527211	475663	415386
7Z	8367	8006	9213	7696	6106	5286	5530	4071	5687	3897
Total	1124945	1095384	1080271	1061179	975557	866419	781363	731725	644220	557929

APPENDIX C. REGRESSION DATA AND RESIDUAL PLOTS

Table 1 Issues against Total OPTEMPO (deployed)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.868559
R Square	0.754395
Adjusted R Square	0.742115
Standard Error	92285.01
Observations	22

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5.23E+11	5.23E+11	61.43163	1.6E-07
Residual	20	1.7E+11	8.52E+09		
Total	21	6.94E+11			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-139139	130075.8	-1.06968	0.297506	-410472	132194.3	-410472	132194.3
Tot OP (D)	48.9186	6.241342	7.837833	1.6E-07	35.89939	61.93781	35.89939	61.93781

RESIDUAL OUTPUT

PROBABILITY OUTPUT

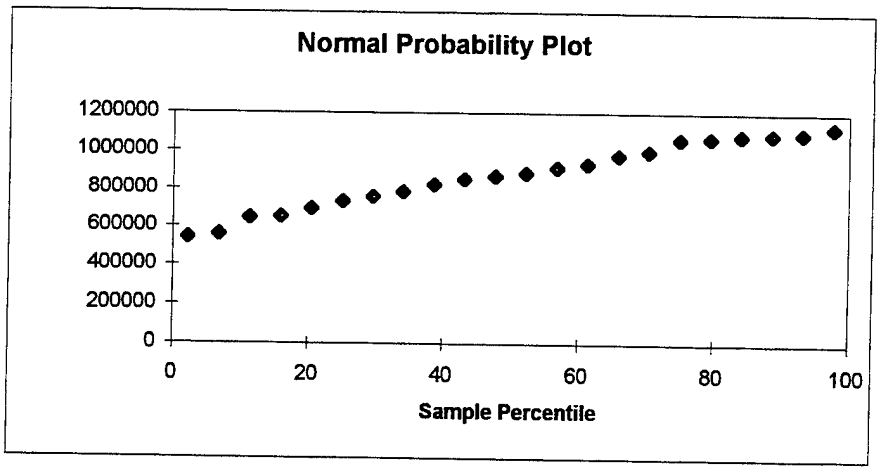
Observation	*Predicted Total Issues*	*Residuals*	*Standard Residuals*	*Percentile*	*Total Issues*
1	655054.6	103245.4	1.118766	2.272727	542019
2	661952.2	-9556.17	-0.10355	6.818182	557929
3	666550.5	25601.48	0.277418	11.36364	644220
4	702965.5	116867.5	1.266375	15.90909	652396
5	750289.4	99269.62	1.075685	20.45455	692152
6	922199.1	-40988.1	-0.44415	25	731725
7	977550.5	-67826.5	-0.73497	29.54545	758300
8	1044300	-112542	-1.2195	34.09091	781363
9	1001154	-2192.75	-0.02376	38.63636	819833
10	1108285	-21278.5	-0.23057	43.18182	849559
11	1001447	66782.74	0.723657	47.72727	866419
12	940421.3	184523.7	1.999498	52.27273	881211
13	1021563	73821.41	0.799929	56.81818	909724
14	1000278	79992.9	0.866803	61.36364	931758
15	1013687	47492.31	0.514626	65.90909	975557
16	996398.9	-20841.9	-0.22584	70.45455	998961
17	1013383	-146964	-1.59251	75	1061179

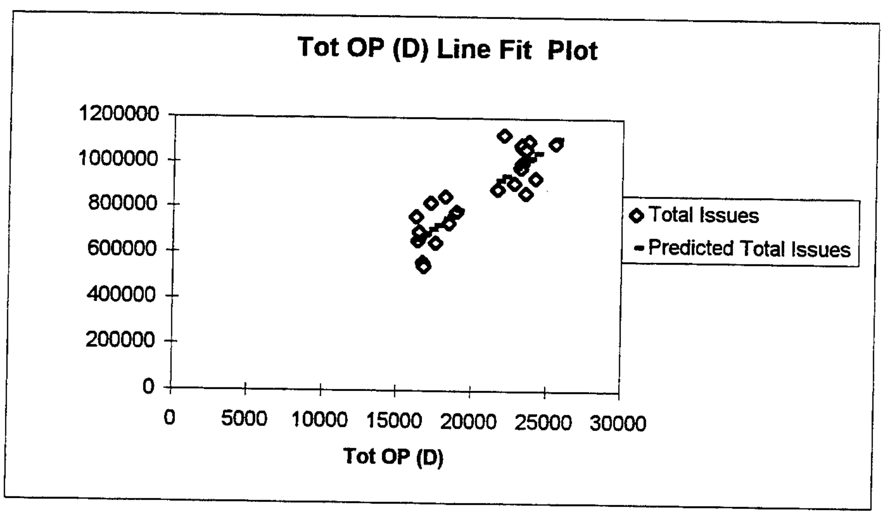
Table 2 Issues against Total OPTEMPO (deployed)

RESIDUAL OUTPUT

PROBABILITY OUTPUT

Observation	*Predicted Total Issues*	*Residuals*	*Standard Residuals*	*Percentile*	*Total Issues*
18	787340.3	-5977.33	-0.06477	79.54545	1068230
19	762616.9	-30891.9	-0.33474	84.09091	1080271
20	720703.4	-76483.4	-0.82877	88.63636	1087007
21	679308.5	-121379	-1.31527	93.18182	1095384
22	682693.7	-140675	-1.52435	97.72727	1124945





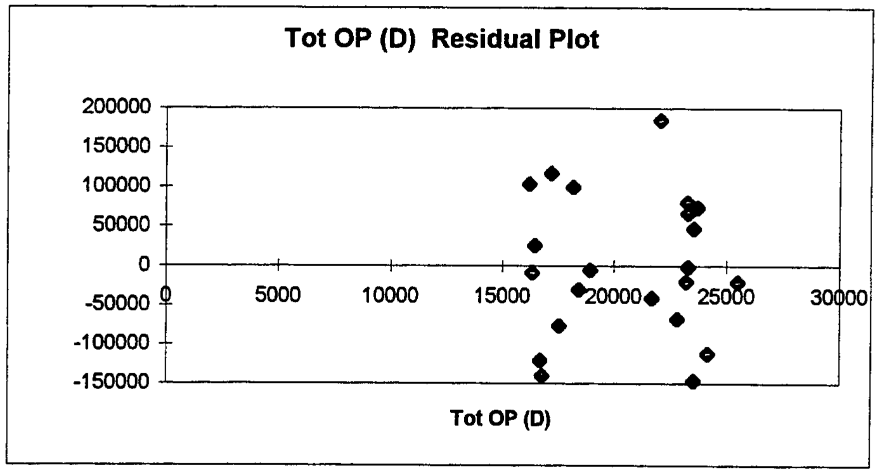

Tot OP (D) Residual Plot
200000
150000
100000
50000
0
-50000
-100000
-150000
0
5000
10000
15000
20000
25000
30000
Tot OP (D)

Table 3 Issues against O&M,N (adjusted)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.899809
R Square	0.809656
Adjusted R Square	0.800138
Standard Error	81242.41
Observations	22

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5.62E+11	5.62E+11	85.07271	1.21E-08
Residual	20	1.32E+11	6.6E+09		
Total	21	6.94E+11			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-148333	111611.6	-1.32901	0.198808	-381150	84484.67	-381150	84484.67
O&m,N (adj)	0.10201	0.01106	9.223487	1.21E-08	0.078939	0.12508	0.078939	0.12508

RESIDUAL OUTPUT

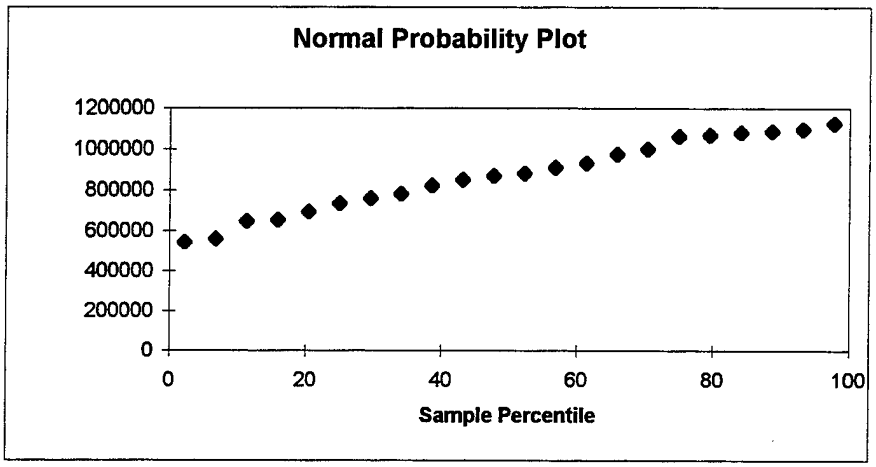
PROBABILITY OUTPUT

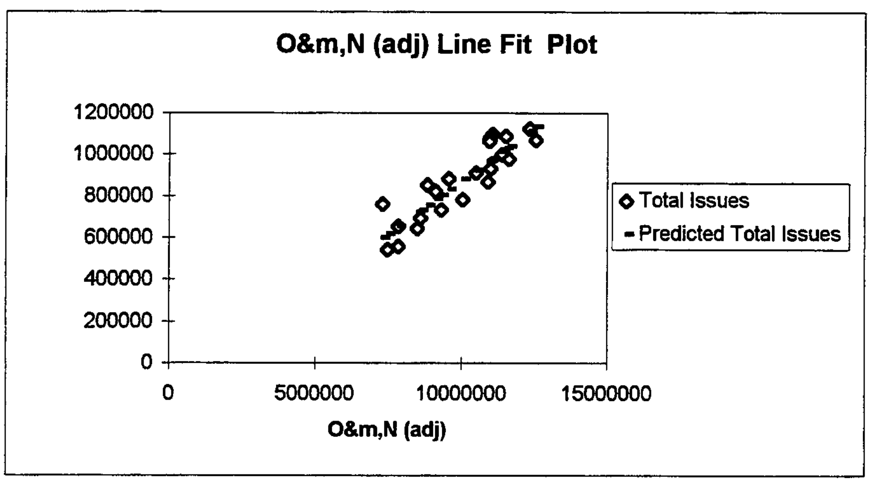
Observation	*Predicted Total Issues*	*Residuals*	*Standard Residuals*	*Percentile*	*Total Issues*
1	596055.1	162244.9	1.997046	2.272727	542019
2	652200.2	195.819	0.00241	6.818182	557929
3	729206.6	-37054.6	-0.4561	11.36364	644220
4	783091.5	36741.52	0.452246	15.90909	652396
5	753920.4	95638.64	1.177201	20.45455	692152
6	828588.9	52622.06	0.647717	25	731725
7	922907.8	-13183.8	-0.16228	29.54545	758300
8	973660.8	-41902.8	-0.51578	34.09091	781363
9	1012691	-13730.1	-0.169	38.63636	819833
10	1027765	59242.43	0.729206	43.18182	849559
11	1133467	-65237.5	-0.803	47.72727	866419

Table 4 Issues against O&M,N (adjusted)

RESIDUAL OUTPUT PROBABILITY OUTPUT

Observation	*Predicted Total Issues*	*Residuals*	*Standard Residuals*	*Percentile*	*Total Issues*
12	1111670	13274.74	0.163397	52.27273	881211
13	979581.2	115802.8	1.425399	56.81818	909724
14	971373.1	108897.9	1.340407	61.36364	931758
15	968475.2	92703.81	1.141077	65.90909	975557
16	1036829	-61272.4	-0.75419	70.45455	998961
17	964845.6	-98426.6	-1.21152	75	1061179
18	877991.7	-96628.7	-1.18939	79.54545	1068230
19	802513.4	-70788.4	-0.87132	84.09091	1080271
20	718072.3	-73852.3	-0.90904	88.63636	1087007
21	650988.6	-93059.6	-1.14546	93.18182	1095384
22	614246.6	-72227.6	-0.88904	97.72727	1124945





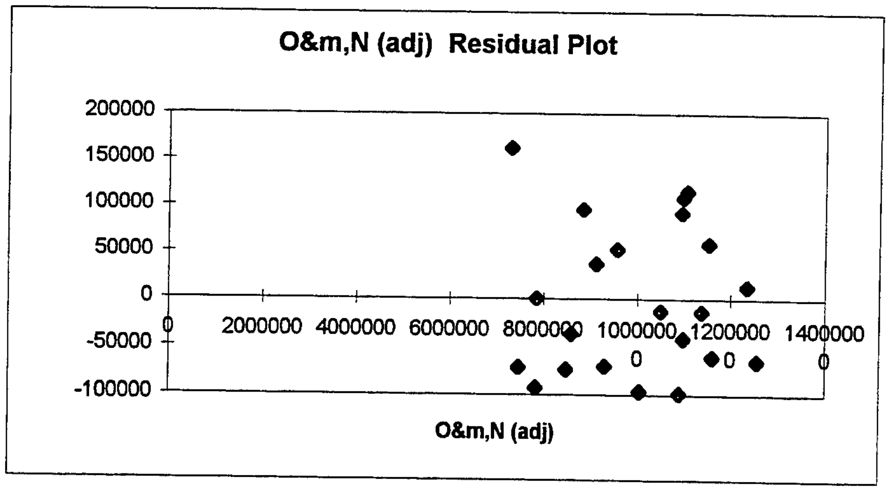

O&m,N (adj) Residual Plot
200000
150000
100000
50000
0
-50000
-100000
0
2000000
4000000
6000000
8000000
10000000
12000000
14000000
O&m,N (adj)

Table 5 Issues against Total OPTEMPO (deployed) and O&M

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.909628
R Square	0.827422
Adjusted R Square	0.809256
Standard Error	79367.63
Observations	22

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	5.74E+11	2.87E+11	45.54764	5.64E-08
Residual	19	1.2E+11	6.3E+09		
Total	21	6.94E+11			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-191951	113408.6	-1.69256	0.106873	-429318	45415.71	-429318	45415.71
O&m,N (adj)	0.070623	0.024907	2.835477	0.010573	0.018492	0.122755	0.018492	0.122755
Tot OP (D)	17.30583	12.37388	1.398577	0.178051	-8.59301	43.20467	-8.59301	43.20467

RESIDUAL OUTPUT

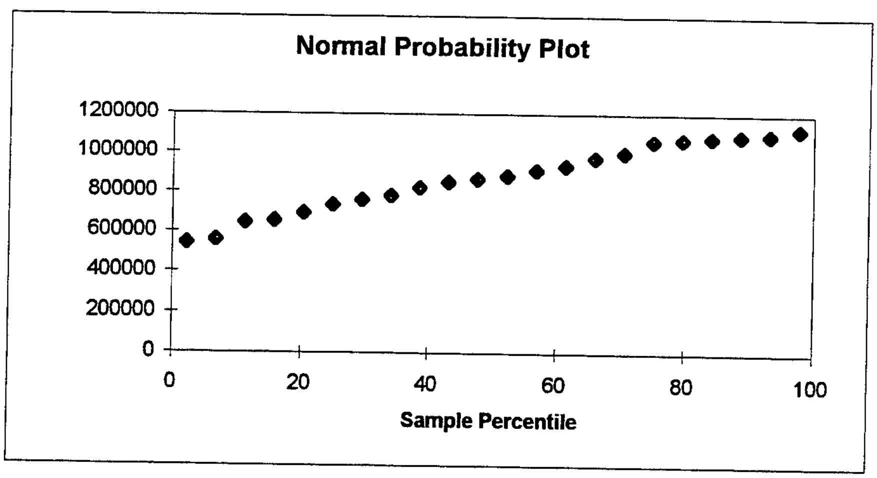
PROBABILITY OUTPUT

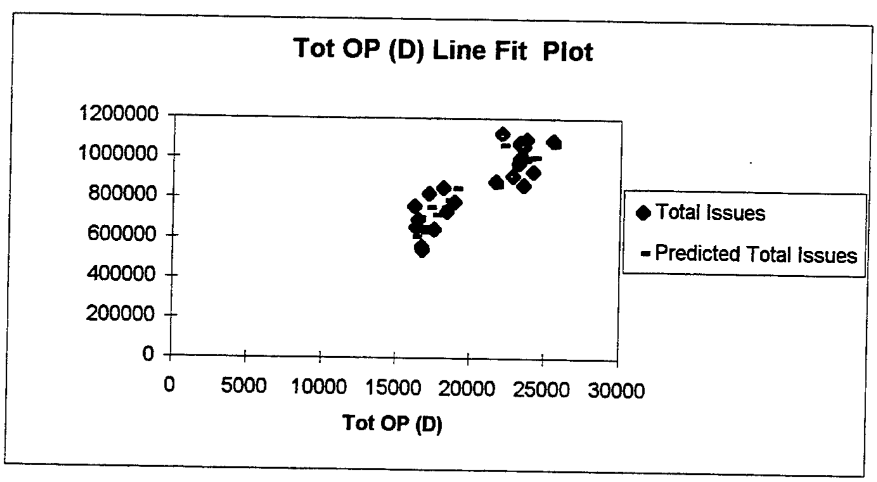
Observation	*Predicted Total Issues*	*Residuals*	*Standard Residuals*	*Percentile*	*Total Issues*
1	604364.1	153935.9	1.939531	2.272727	542019
2	645674.6	6721.434	0.084687	6.818182	557929
3	700614.5	-8462.48	-0.10662	11.36364	644220
4	750802.5	69030.46	0.869756	15.90909	652396
5	747348.4	102210.6	1.287812	20.45455	692152
6	859859.2	21351.81	0.269024	25	731725
7	944739.6	-35015.6	-0.44118	29.54545	758300
8	1003491	-71732.8	-0.9038	34.09091	781363
9	1015249	-16287.6	-0.20522	38.63636	819833
10	1063584	23423.01	0.29512	43.18182	849559
11	1098968	-30738.4	-0.38729	47.72727	866419
12	1062289	62656.31	0.789444	52.27273	881211
13	999545.9	95838.15	1.207522	56.81818	909724

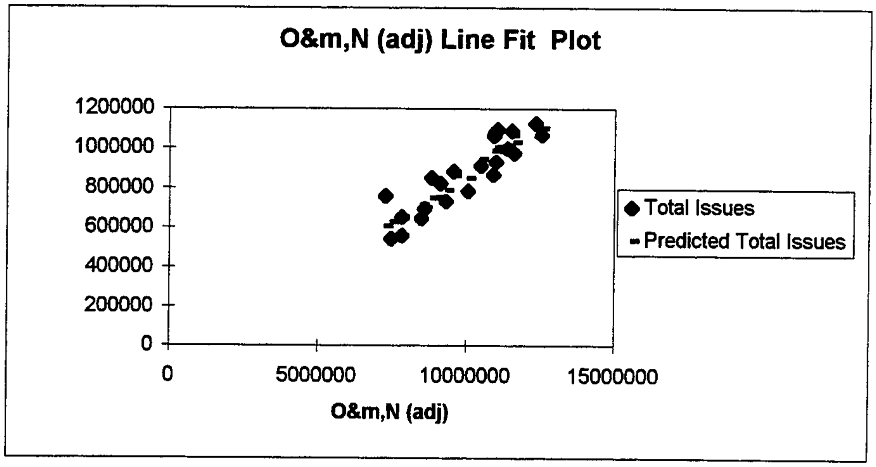
Table 6 Issues against Total OPTEMPO (deployed) and O&M

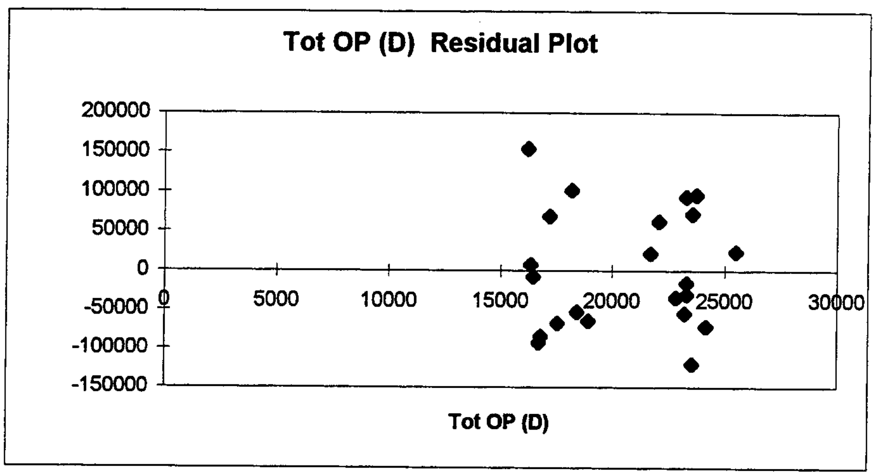
RESIDUAL OUTPUT — PROBABILITY OUTPUT

Observation	*Predicted Total Issues*	*Residuals*	*Standard Residuals*	*Percentile*	*Total Issues*
14	986333.5	93937.51	1.183575	61.36364	931758
15	989070.7	72108.29	0.908535	65.90909	975557
16	1030278	-54720.9	-0.68946	70.45455	998961
17	986450.6	-120032	-1.51235	75	1061179
18	846353.1	-64990.1	-0.81885	79.54545	1068230
19	785351.5	-53626.5	-0.67567	84.09091	1080271
20	712063.5	-67843.5	-0.8548	88.63636	1087007
21	650975.9	-93046.9	-1.17235	93.18182	1095384
22	626736.2	-84717.2	-1.0674	97.72727	1124945






O&m,N (adj) Line Fit Plot
1200000
1000000
800000
600000
400000
200000
0
0
5000000
10000000
15000000
O&m,N (adj)
Total Issues
Predicted Total Issues


Tot OP (D) Residual Plot
200000
150000
100000
50000
0
-50000
-100000
-150000
0
5000
10000
15000
20000
25000
30000
Tot OP (D)

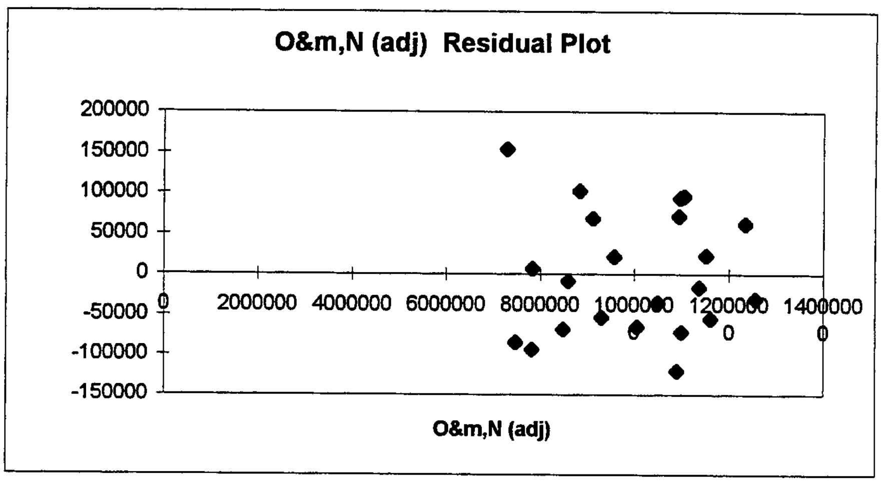

O&m,N (adj) Residual Plot
200000
150000
100000
50000
0
-50000
-100000
-150000
0
2000000
4000000
6000000
8000000
10000000
12000000
14000000
O&m,N (adj)

Table 7 Workload against total OPTEMPO (deployed)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.895249
R Square	0.801471
Adjusted R Square	0.702207
Standard Error	742336.2
Observations	4

Year	Workload	Tot OP (D)
1993	7877329	18433.8
1994	6461678	17577
1995	5958641	16730.8
1996	4583537	16800
1997		16424.1
1998		16372.5
1999		16428

ANOVA

	df	SS	MS	F	Significance F
Regression	1	4.45E+12	4.44934E+12	8.0741065	0.1047507
Residual	2	1.1E+12	5.51063E+11		
Total	3	5.55E+12			

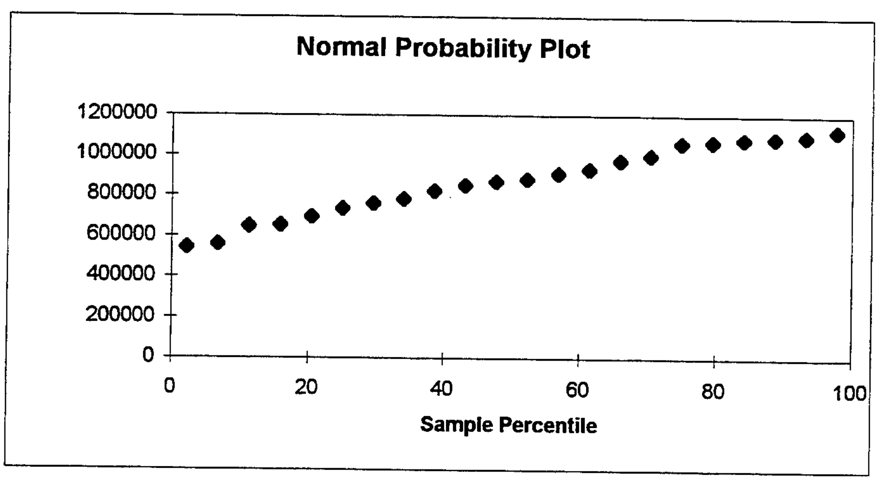
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%
Intercept	-2E+07	9352911	-2.17419358	0.1617304	-60577395	19907317	-60577394.9
Tot OP (D)	1527.45	537.5512	2.841497236	0.1047507	-785.4475	3840.3482	-785.447548

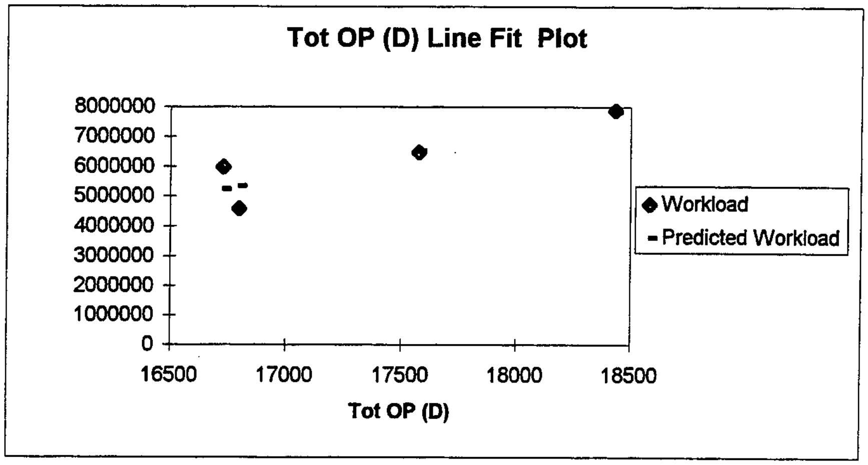
RESIDUAL OUTPUT

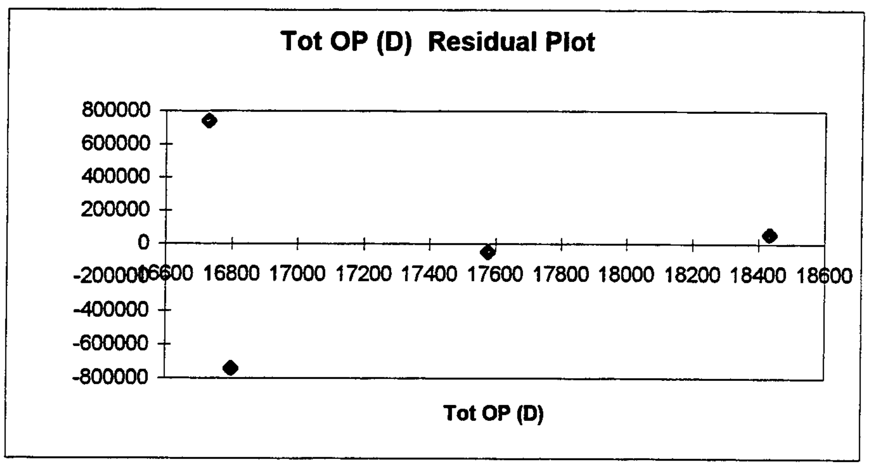
Observation	Predicted Workload	Residuals	Standard Residuals
1	7821675	55653.81	0.074971168
2	6512956	-51277.7	-0.06907617
3	5220427	738213.7	0.994446712
4	5326127	-742590	-1.00034171

PROBABILITY OUTPUT

Percentile	Workload
12.5	4583537
37.5	5958641
62.5	6461678
87.5	7877329




Tot OP (D) Line Fit Plot
8000000
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
16500
17000
17500
18000
18500
Tot OP (D)
Workload
Predicted Workload


Tot OP (D) Residual Plot
800000
600000
400000
200000
0
-200000
-400000
-600000
-800000
16600 16800 17000 17200 17400 17600 17800 18000 18200 18400 18600
Tot OP (D)

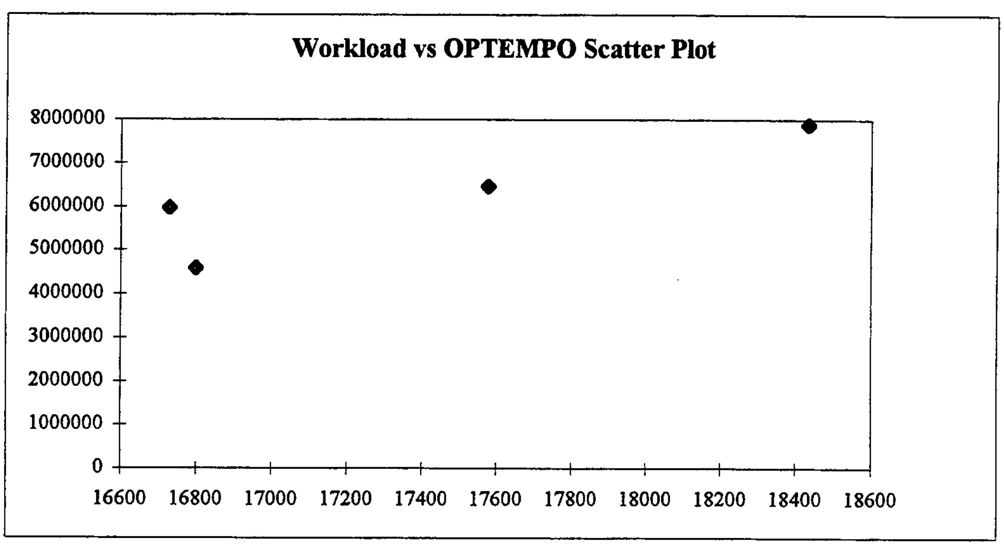

Workload vs OPTEMPO Scatter Plot
8000000
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
16600 16800 17000 17200 17400 17600 17800 18000 18200 18400 18600

Table 8 Workload against O&M (adjusted)

SUMMARY OUTPUT

Year	Workload	O&m,N (adj)
1993	7877329	9321132.
1994	6461678	8493357.
1995	5958641	7835737.
1996	4583537	7475555.
1997		6790972.
1998		6964198.
1999		6671012.

Regression Statistics	
Multiple R	0.96957
R Square	0.940065
Adjusted R Square	0.910098
Standard Error	407876.3
Observations	4

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5.22E+12	5.22E+12	31.36958	0.03043
Residual	2	3.33E+11	1.66E+11		
Total	3	5.55E+12			

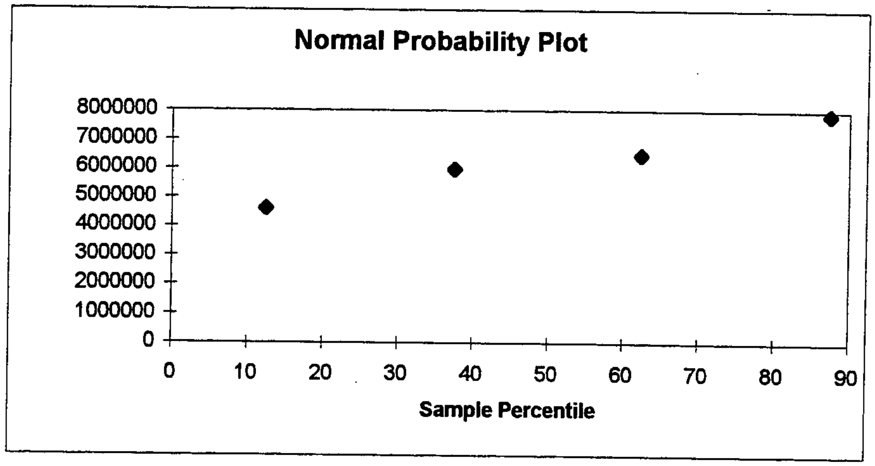
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-7245088	2412800	-3.00277	0.095314	-1.8E+07	3136359	-1.8E+07	3136359
O&m,N (adj)	1.62597	0.290307	5.600856	0.03043	0.376877	2.875063	0.376877	2.875063

RESIDUAL OUTPUT

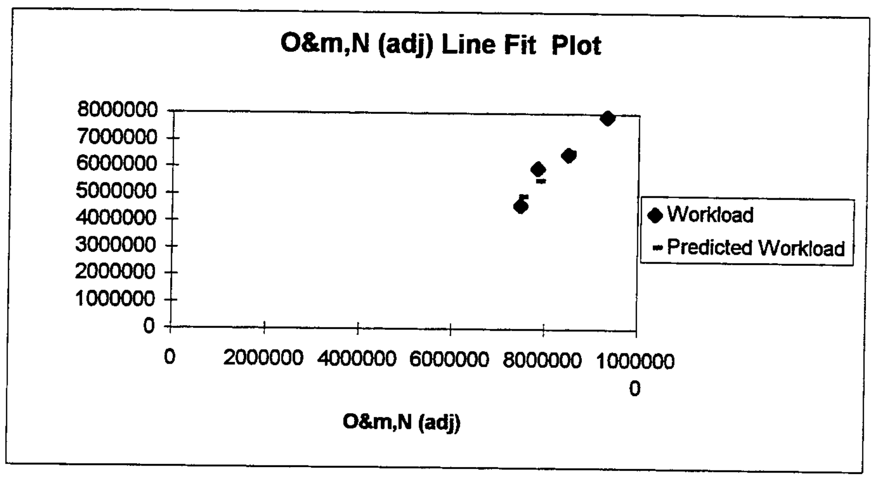
Observation	*Predicted Workload*	*Residuals*	*Standard Residuals*
1	7910796	-33467.2	-0.08205
2	6564858	-103180	-0.25297
3	5495587	463053.8	1.13528
4	4909943	-326406	-0.80026

PROBABILITY OUTPUT

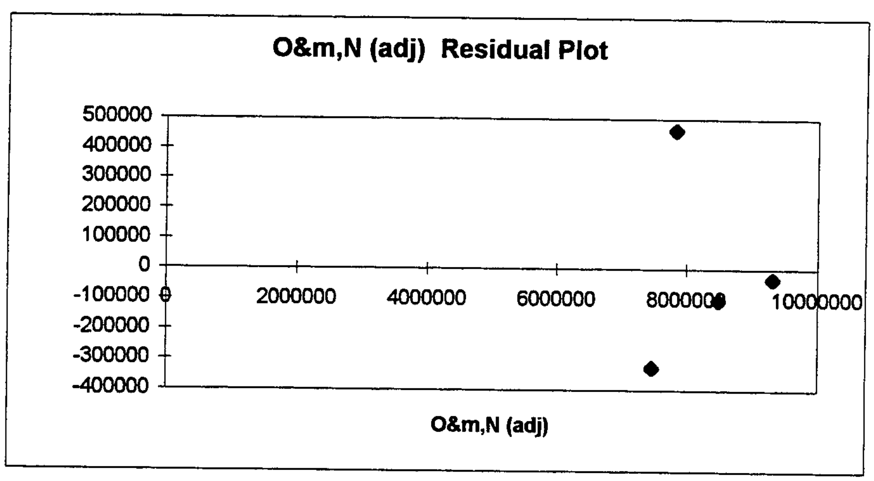
Percentile	*Workload*
12.5	4583537
37.5	5958641
62.5	6461678
87.5	7877329



Normal Probability Plot
8000000
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
0
10
20
30
40
50
60
70
80
90
Sample Percentile



O&m,N (adj) Line Fit Plot
8000000
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
0
2000000
4000000
6000000
8000000
1000000
0
Workload
Predicted Workload
O&m,N (adj)



O&m,N (adj) Residual Plot
500000
400000
300000
200000
100000
0
-100000
-200000
-300000
-400000
0
2000000
4000000
6000000
8000000
10000000
O&m,N (adj)

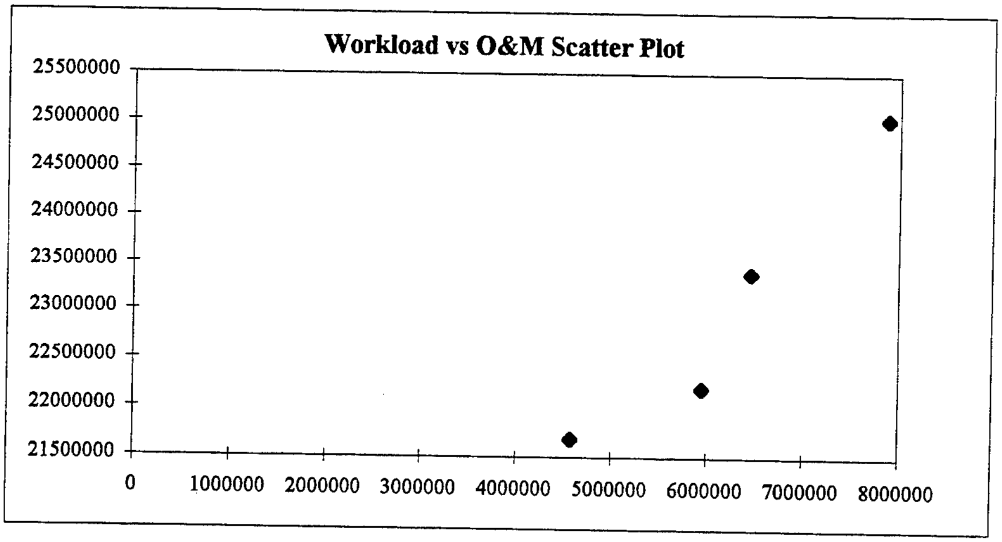

Workload vs O&M Scatter Plot
25500000
25000000
24500000
24000000
23500000
23000000
22500000
22000000
21500000
0
1000000
2000000
3000000
4000000
5000000
6000000
7000000
8000000

Table 9 Workload against total OPTEMPO (deployed) and O&M (adjusted)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.998057
R Square	0.996117
Adjusted R Square	0.988351
Standard Error	146818
Observations	4

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	5.53E+12	2.76E+12	128.2713	0.062313
Residual	1	2.16E+10	2.16E+10		
Total	3	5.55E+12			

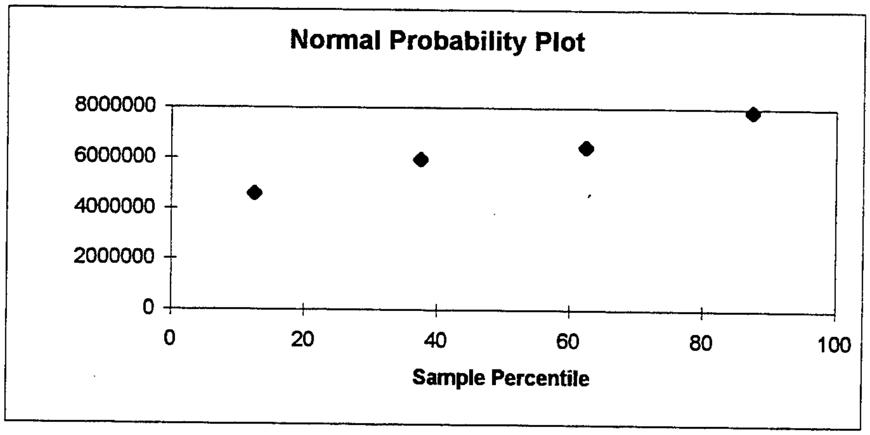
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	10353609	4712635	2.196989	0.271928	-5E+07	70233055	-5E+07	70233055
O&m,N (adj)	3.415058	0.482337	7.080228	0.089324	-2.71359	9.543708	-2.71359	9.543708
Tot OP (D)	-1864.49	490.7275	-3.79944	0.16384	-8099.75	4370.766	-8099.75	4370.766

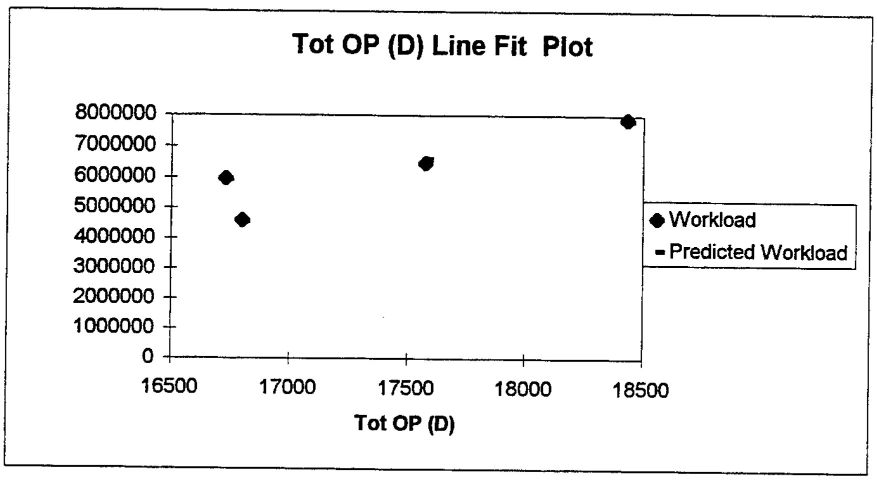
RESIDUAL OUTPUT

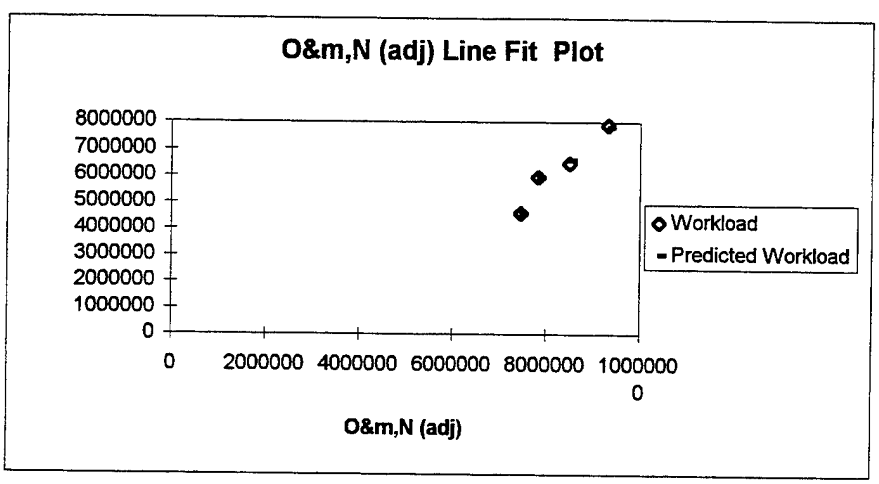
Observation	*Predicted Workload*	*Residuals*	*Standard Residuals*
1	7816154	61174.59	0.41667
2	6586750	-125072	-0.85189
3	5918671	39969.69	0.27224
4	4559609	23927.98	0.162977

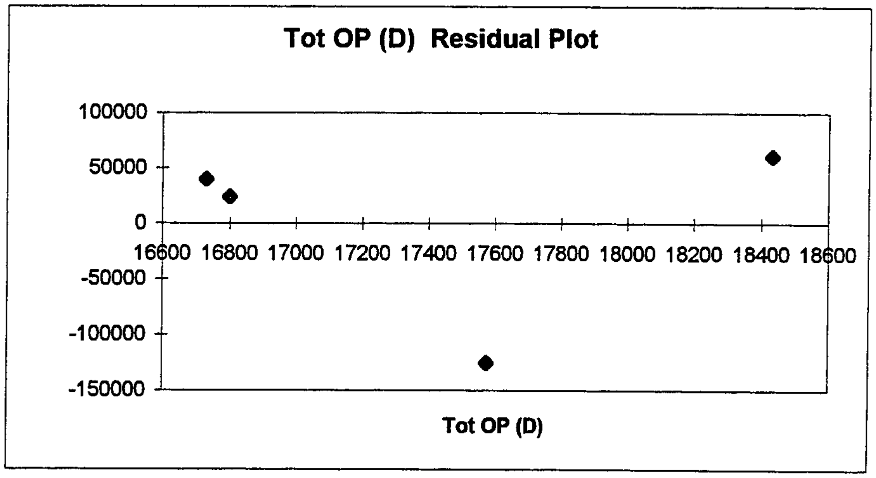
PROBABILITY OUTPUT

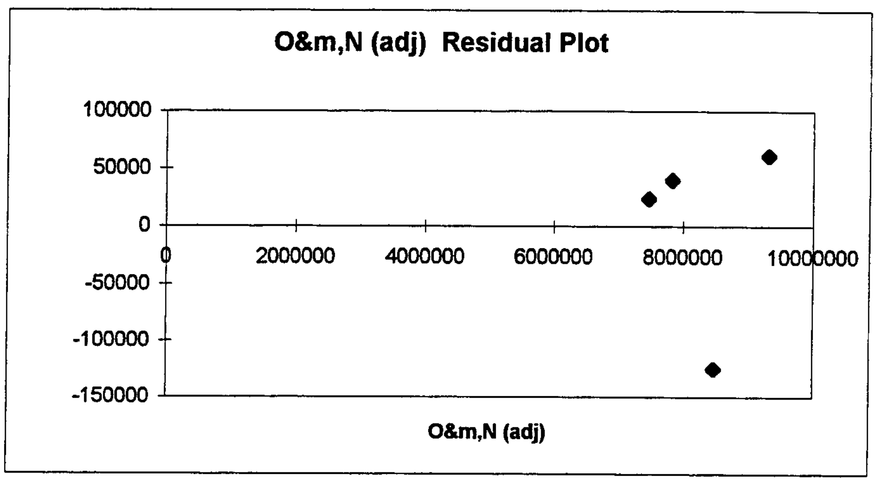
Percentile	*Workload*
12.5	4583537
37.5	5958641
62.5	6461678
87.5	7877329


Normal Probability Plot
8000000
6000000
4000000
2000000
0
0
20
40
60
80
100
Sample Percentile


Tot OP (D) Line Fit Plot
8000000
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
16500
17000
17500
18000
18500
Tot OP (D)
Workload
Predicted Workload


O&m,N (adj) Line Fit Plot
8000000
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
0
2000000
4000000
6000000
8000000
1000000
0
O&m,N (adj)
Workload
Predicted Workload


Tot OP (D) Residual Plot
100000
50000
0
-50000
-100000
-150000
16600 16800 17000 17200 17400 17600 17800 18000 18200 18400 18600
Tot OP (D)


O&m,N (adj) Residual Plot
100000
50000
0
-50000
-100000
-150000
0 2000000 4000000 6000000 8000000 10000000
O&m,N (adj)

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INDEX OF TERMS

α	Intercept (Regression Coefficient)
β	Slope (Regression Coefficient)
Y	Dependent Variable
X	Independent Variable
ε_I	Error Term
adj.	Adjusted
CIT	Consumable Item Transfer
COG	Cognizance Groups
COSAL	Consolidated Shipboard Allowance List
DBOF	Defense Business Operating Fund
DLA	Defense Logistics Agency
DOD	Department of Defense
DW	Durbin-Watson
FISC	Fleet Industrial Support Centers
FOO	Follow-On Outfitting
GSA	General Services Administration
ICP	Inventory Control Point
MIS	Management Information System
NAVICP	Naval Inventory Control Point
NAVSUP	Naval Supply Systems Command

NPCI	Net Price Change Impact
NRD	Non-Recurring Demand
O&M	Operations and Maintenance
O&M,N	Operations and Maintenance, Navy
OPTEMPO	Operating Tempo
Perstrength	Personnel End Strength
SAMMS	Standard Automatic Materiel Management System.

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